Towards an AI-Empowered Multimodal Pain Assessment Tool for Cancer-Related Pain

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Preface

With the completion of this thesis, my time as a student comes to an end. It was a seven-year journey in which I have had the opportunity to learn, explore, and experience so much. It all began with my Bachelor's in Clinical Technology, a programme that bridges the gap between technology and medicine and introduced me to the world of medical innovations. I then took part in Project MARCH, where I discovered the immense value of collaboration with people from diverse disciplines. After a year, I continued my studies in the Master's in Technical Medicine, further specialising at the intersection of technology and healthcare and developing my skills as an engineer, designer, and medical professional.

Looking back, I realise how much these years have meant to me. The start was unfamiliar, filled with new experiences and an overwhelming number of choices. Over time, I learned to seize opportunities, find my own path, and grow in both knowledge and confidence. I discovered that I enjoy learning most when it's connected to real-world challenges and when I can collaborate with others toward a shared goal.

Of course, not everything went smoothly. The decisions and setbacks I faced – both personally and within my family – sometimes threw me off balance. Yet, I emerged stronger, and these experiences have shaped me into the person I am today – someone who is happy with herself and the people around her, and who truly enjoys life. These challenges have made me more aware of all the good things in life. The fact that I will soon be able to celebrate my graduation with my entire family and circle of friends is incredibly valuable to me, making the conclusion of this chapter even more special.

I look back with pride on everything I have done and achieved. I am deeply grateful to everyone who has supported, guided, and inspired me. My supervisors, Mark Mulder and Helma Torkamaan, for their immense trust in me and for providing direction when I lost it (again). My friends, for the endless laughter, much-needed relaxation, and our spontaneous plans. And my family and dear partner, for their unconditional support, genuine interest, listening ear, and countless warm hugs.

This thesis marks the end of a remarkable phase and the beginning of a new one: my life as a PhD candidate. With pride and gratitude, I present the result of my work and look forward to what the future will bring.

Marsha

Summary

Introduction

Cancer-related pain is a prevalent and under-assessed issue in oncological care. Despite the availability of effective pain treatments, challenges in pain assessment - such as communication barriers, subjective interpretation, and workflow constraints - continue to hinder accurate pain recognition and management. In recent years, advances in artificial intelligence (AI), sensor technology and mobile health have offered promising new opportunities for more consistent, continuous and context-aware assessment strategies. Facial expressions and vocal cues have been identified as promising behavioural indicators of pain, and their use in automatic pain assessment (APA) is gaining increasing attention.

To explore how such technologies could support cancer pain assessment and management, the SENSAI project was initiated. The project focuses on the development of a human-centred, AI-empowered tool for APA in cancer care, based on facial expressions and vocal cues captured through a mobile application.

This thesis presents the initial steps of the SENSAI project. Its objectives were to examine current pain assessment practices and challenges in oncology, investigate end-user perspectives on AI-supported assessment, translate research insights into a conceptual tool framework, support the design of a user-centred APA application, and initiate the development of a multimodal cancer-related pain database.

Methodology

A multiphase, design-oriented research approach was used, guided by user-centred design, the Double Diamond framework, and a translational AI development model for healthcare. This thesis encompassed the Research and Conceptualisation phases and initiated the Development phase.

In the research phase, background studies and an exploratory interview study with oncologists were conducted to understand current pain assessment practices and challenges. This informed the problem definition and supported the development of an initial concept for the tool In the conceptualisation phase, this concept was refined into was structured framework. The second part of the interview study explored oncologists' attitudes towards the proposed APA tool, guided by the mobile health Technology Acceptance Model. These findings, along with expert consultations, a brainstorm session and feasibility considerations, shaped the envisioned design and functionalities of the tool. In the development phase, agile application development was initiated in collaboration with software company Innovattic, with the author serving as product owner. In

parallel, a clinical study protocol was prepared for the creation of a multimodal cancer-related pain dataset to support future AI model training.

Results

The interview study identified five key challenges in current cancer pain assessment: the complexity and subjectivity of pain, ambiguity in responsibility, communication barriers, balancing all pain information with clinical judgement to come to decision-making, and practical constraints. Oncologists expressed conditional interest in an APA tool, emphasising the importance of clinical validation, interpretability, and seamless integration. The conceptual framework proposed three core functionalities: multimodal data collection via a mobile application, AI-based pain classification, and feedback for both patients and clinicians. The mobile application is currently under development and includes measurement and login/authentication modules. A clinical protocol for database development has been submitted for ethical review.

Conclusion

This thesis establishes a solid interdisciplinary foundation for the development of a human-centred APA tool tailored to cancer care. While the AI model itself lies beyond the scope of this thesis, the design process, stakeholder engagement, and technical groundwork contribute to a clinically grounded and ethically aligned vision for future development. The work advances efforts to improve how cancer-related pain is recognised, communicated, and managed in clinical practice. Building on this foundation, future research should focus on user testing with patients, iterative refinement of the application and measurement protocol, technical development of the AI model, and broader clinical evaluation to assess its impact on care delivery and patient experience.

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List of Abbreviations

A	Attitude towards Technology
AI	Artificial Intelligence
APA	Automatic Pain Assessment
API	Application Programming Interface
AU	Action Unit
BI	Behavioural Intension
CV	Cross-Validation
DL	Deep Learning
DMP	Data Management Plan
EMC	Erasmus University Medical Centre
EMR	Electronic Medical Record
FACS	Facial Action Coding System
GDPR	General Data Protection Regulation
HCAI	Human-Centred Artificial Intelligence
i-PANAS-SF	international Positive and Negative Affect Scale - Short Form
IASP	International Association for the Study of Pain
ID	Identification number
ISS	Intelligent Sight and Sound
mHealth	Mobile Health
ML	Machine Learning
MoSCoW	Must-have, Should-have, Could-have, Won't have
mTAM	Mobile health Technology Acceptance Model
MVP	Minimum Viable Product
NFK	Nederlandse Federatie van Kankerpatiëntenorganisaties
NRS	Numerical Rating Scale
PEOU	Perceived Ease of Use
PR	Perceived Risks
PU	Perceived Usefulness

SENSAI	Seeing, hEaring, seNsing: Smart, effortless, and objective pain assessment with mobile AI technology
SVM	Support Vector Machine
T	Trust
TA	Thematic Analysis
TAM	Technology Acceptance Model
U	Use of Technology
UCD	User-Centred Design
UI	User Interface
UX	User experience
VAS	Visual Analogue Scale
WHO	World Health Organisation
2FA	Two-Factor Authentication

1 Introduction

Pain is a universal human experience [1], yet for cancer patients, it often becomes a defining and debilitating aspect of their journey [2]. Cancer pain can significantly diminish quality of life [3], affecting not only the physical well-being of patients but also their psychological and emotional health [4]. Despite advancements in medical treatments, effective pain management remains a significant challenge, particularly due to the struggles that both patients and healthcare providers face with accurate pain assessment [5]. Traditional methods, such as self-reports and clinician observations, are subjective and prone to misinterpretation, leading to under- and overtreatment [6, 7].

Recent developments in artificial intelligence (AI) have opened new possibilities for enhancing pain assessment. AI models, particularly those that integrate multimodal data, such as facial expressions, voice patterns, and physiological signals, have the potential to provide more consistent pain assessments. However, the integration of AI for automatic pain assessment (APA) in clinical settings remains underexplored, especially for cancer patients. The ability to develop an AI tool that can assess pain automatically and accurately is of great interest, as it could provide both patients and clinicians with a valuable tool to better understand and manage cancer-related pain.

With this in mind, the SENSAI-project (Seeing, hEaring, seNsing: Smart, effortless, and objective pain assessment with mobile AI technology) was initiated by M. Mulder, an oncologist at the Department of Oncology at Erasmus Medical Centre, in collaboration with H. Torkamaan, an assistant professor in AI for Health Systems at the Multi-Actor Systems Department of Delft University of Technology. The project aims to develop an innovative, AI-driven approach to pain assessment through multimodal data analysis, integrating facial expressions and voice patterns to

enhance the objectivity and accuracy of pain evaluation. The project follows a structured research trajectory to ensure the feasibility, acceptance, and effectiveness of AI-based pain assessment in clinical practice. The project is divided into several key phases: 1) context analysis and implementation scope, 2) conceptualisation based on end-user acceptance and requirements, 3) development of core components, including a multimodal database, an AI-APA model and mobile and web-based applications, and 4) clinical validation and feasibility studies.

This thesis focuses on the initial phases of the project, exploring the clinical context for AI-driven pain assessment, assessing end-user perspectives, and outlining the foundational steps toward developing the multimodal database and AI model. By addressing these early-stage components, this work contributes to the groundwork necessary for future technical development and clinical validation.

1.1 Problem Statement

Each year, over ten million people worldwide are diagnosed with cancer [8]. For the majority, pain becomes one of the most distressing and pervasive symptoms [9], significantly impacting their quality of life. The International Association for the Study of Pain (IASP) defined pain as "an unpleasant sensory and emotional experience associated with, or resembling that associated with, actual or potential tissue damage" [10 (p. 1977)]. This definition highlights the multidimensional nature of pain, encompassing not only physical sensations but also the emotional and psychological burden it imposes. For cancer patients, these dimensions intertwine, often amplifying the suffering already caused by their disease.

After decades of advancements in pain management, there is a consensus among experts that most patients can be well-treated for their pain using knowledge, medications and techniques that are readily accessible [11]. Nevertheless, over one-third of cancer patients continue to experience moderate to severe pain during their illness [12]. In the Netherlands, this figure rises to nearly 45% [13]. These statistics underscore a critical issue: pain is often underestimated, poorly assessed, and insufficiently treated, leaving many patients to suffer unnecessarily.

Effective pain management begins with accurate and consistent pain assessment [14, 15], as it is an important step in early diagnosis, monitoring disease progression, tailoring treatment plans, and evaluating the effectiveness of interventions [16]. Yet, this remains a complex and unresolved challenge. Pain is not a simply matter of intensity, nor a singular or uniform experience [17, 18]. Rather, it is a multifaceted phenomenon that can vary in form and intensity [17] across individuals and affect the body in multiple ways. Cancer pain, in particular, affects interconnected dimensions, such as the sensory-discriminative, cognitive, emotional, and behavioural [19], that evolve with disease progression. Simultaneously, physiological, psychological and emotional factors such as personality [20], past painful experiences [21], and social context [22], influence the experience of pain. For example, for cancer patients, this means that pain may be influenced by not only the physical progression of the disease, but also by psychological conditions such as anxiety and depression, emotional responses like fear and helplessness, and past experiences with

pain. These individual differences make it exceptionally difficult to develop a standardized approach to pain management that can effectively address the diverse needs of patients.

Current pain assessment approaches often rely on self-reports, such as the Numerical Rating Scale (NRS) [23]. This tool asks patients to quantify their pain on a numerical scale. While self-report methods are simple, proven valuable and widely adopted due to its simplicity, their usefulness is limited. This method relies on subjective inputs and faces difficulties with interpretation and application. For example, patients may underreport or overreport their pain due to emotional distress [24], fear of judgment, cultural norms [25], or simply because they are unable to articulate their experience fully. Clinicians, on the other hand, are often constrained by time, expertise, and the complexity of interpreting verbal and non-verbal cues [26]. In outpatient settings, which are becoming increasingly common due to improvements in treatment options, limited hospital resources, and the growing number of patients, these challenges are further amplified [27]. As more cancer patients are treated outside of hospitals or in less intensive care environments, physicians typically see them infrequently and for brief appointments that address multiple aspects of care beyond pain management. This can lead to difficulties in accurately assessing pain intensity or detecting changes over time, resulting in delays in treatment adjustments and ultimately, suboptimal pain management. All together, these challenges lead to under- and overtreatment of pain [6, 7], both of which have significant consequences for patients and healthcare systems alike.

Advances in AI and audiovisual data analysis offer an opportunity to address these limitations. AI-based APA models can estimate pain intensity by analysing measurable indicators such as facial expressions and vocal patterns. This cutting-edge approach aims to enhance both the accuracy and efficiency of evaluating pain levels, offering promising prospects for improving pain management and patient care. Preliminary studies [28–31] have shown encouraging results, suggesting that such tools could offer scalable, affordable, and patient-centred solutions.

Despite this potential, clinical implementation remains limited, with only one known commercially available tool designed for patients with dementia [32]. To date, no publicly available AI-based pain assessment tool has been developed specifically for cancer patients. Current AI-based APA models face several challenges that hinder their widespread adoption in clinical settings. These include issues related to usability, interpretability, and integration into existing healthcare workflows as found in my earlier literature study. Furthermore, existing APA models are typically trained on general pain datasets, which fail to capture the unique nature of cancer pain. This lack of tailored datasets and validation in real-world clinical settings further hinders their effectiveness and reliability for cancer patients.

To bridge these gaps, there is a pressing need for research that prioritises not only technical advancements but also human-centred design principles in the development of APA models. This means involving patients and clinicians throughout the process – ensuring that the technology aligns with their needs, expectations, and real-world clinical applications. A human-in-the-loop approach, where users provide input at various stages of model development, is essential for fostering trust, improving usability, and making APA models more interpretable and actionable in practice. By embedding AI into a framework that enhances, rather than replaces, human

judgement, such technology has the potential to empower patients in expressing their pain more effectively while supporting clinicians in making informed decisions.

This thesis takes the first steps toward developing a clinically relevant and patient-friendly AI-based APA tool for cancer patients. It does so by examining the context and challenges of pain assessment, exploring the perspectives and needs of future end-users, starting with the design and development of the tool and contributing to the development of a new dataset tailored to cancer pain. Central to this approach is a human-in-the-loop design, ensuring that patients and clinicians play an active role in shaping the technology. By prioritising user-centric development, this research aims to lay the foundation for an AI-driven tool that enhances pain assessment, supports clinical decision-making, and ultimately empowers patients in managing their pain. In doing so, it contributes to the evolving landscape of personalised and data-driven pain management in oncology.

1.2 Objectives

As part of the broader SENSAI project, this thesis aims to take the first steps toward developing a clinically relevant and human-centred AI-based APA tool for cancer related-pain. To achieve this, the following sub-objectives have guided this research:

1. *Explore current pain assessment practices and challenges in oncology*
2. *Investigate end-user perspectives on AI-assisted pain assessment*
3. *Translate research insights into a conceptual framework for tool development*
4. *Support the development of a user-centred APA-application*
5. *Develop the research protocol for a multimodal database development study*

1.3 Research Methodology

This project follows an applied, design-oriented research approach aimed at developing a clinically relevant and human-centred AI-based tool for cancer-related pain assessment. To ensure both, scientific rigour and practical relevance, the project integrates complementary principles of user-centred design [33], the Double Diamond framework [34] and an established healthcare-oriented AI development approach [35]. User-centred design ensures continuous involvement of patients and oncologists aligning the tool with real-world needs. The Double Diamond framework structures the design process into four iterative phases: Discover, Define, Develop, and Deliver. Each pair of phases alternates between divergent thinking—broadly exploring challenges or potential solutions—and convergent thinking—narrowing down insights to inform focused design decisions. In parallel, the translational AI development framework guides the technical trajectory of the project, from problem selection and data collection to model validation and deployment.

The thesis covers the first two phases - Research and Conceptualisation - and the beginning of the third phase – Development – of the project. These phases are visualised in Figure 1 and described below.

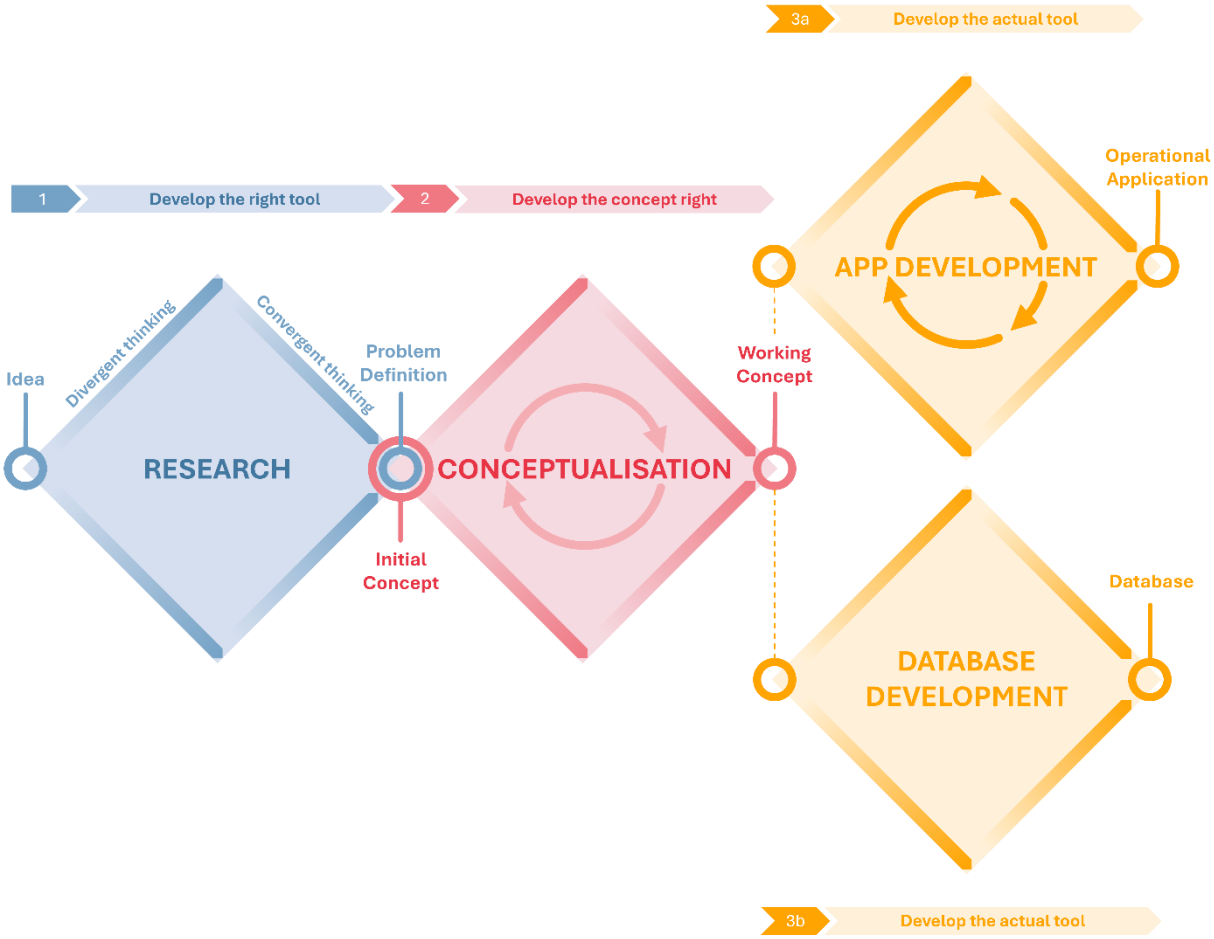

Figure 1 - The three phases of the applied research. The research phase is focused on understanding the problem space through divergent and convergent thinking. Next, the conceptualisation phase translates initial insights into a structured, stakeholder-informed tool concept. These two phases reflect the principle of developing the right tool. The process then transitions into the development phase, aligned with developing the concept right. In this phase, two parallel tracks were initiated: app development, focusing on the technical implementation of the mobile and researcher-facing applications, and database development, aimed at creating a high-quality multimodal dataset for future model training. This visual representation also highlights the iterative loops within each phase and the progressive refinement from idea to operational tool.

1. Research Phase: From Idea to Problem Definition and Initial Concept
   The first phase focused on shaping the problem definition and forming an initial concept for the tool. This phase involved discussions with experts in the field and the formation of a research group. Additionally, to deepen our understanding of the current challenges in pain assessment in oncology, an exploratory interview study with cancer patients and oncologists was conducted. Together, this first part of this study aimed to understand current pain assessment practices and challenges in oncology.
2. Conceptualisation Phase: From Initial Concept to a Conceptual Framework
   The second phase focused on refining the tool from an initial concept into a more structured and actionable working model. As part of this phase, the second part of the interview study was conducted to explore oncologists' attitudes towards the proposed tool, as well as their preferences and requirements for its development and implementation. To further strengthen the design, expert consultations were held and a dedicated brainstorm session with the research team was conducted. These insights – together with findings

from the earlier technical literature review and feasibility considerations – were synthesised into a conceptual framework to guide the tool's further development and design.

3. Development Phase: Building the Tool
   The third phase involved the actual development of the tool. For the project this was divided into three key components: application development, database development and AI-model development. The start of two of these are covered in this thesis:
   a. *Application development*: Conducted in collaboration with Innovattic (a software company in Delft, The Netherlands), focusing on designing and building the mobile and web-based platform for the tool.
   b. *Database development*: A clinical study protocol was developed to establish the dataset needed for AI model development.

1.4 Scope and Limitations

The scope of this thesis encompasses the development of an AI-based APA tool for a specific population: cancer patients, who experience cancer-related pain or cancer-treatment-related pain. The research and development focusses on the use of audiovisual data, specifically facial expressions and paralinguistic patterns, to enable the AI model to capture multidimensional indicators of pain. These modalities have been selected for their potential to provide rich, non-invasive insights into patients' pain experiences. In order to allow for future expansion of the input data modalities, the model development is designed with a modular architecture. The study prioritises the creation of a high-quality dataset collected in inpatient settings, which serves as the foundation for training and validating an AI model. The ultimate vision is to implement the tool in outpatient and ambulatory care, addressing gaps in current pain assessment methods. However, full clinical deployment and real-world testing are beyond the project's timeline.

This thesis operates within several constraints that must be considered when interpreting the findings. First, while each phase of this thesis presents initial conclusions, the research is ongoing. The exploratory interview study will continue beyond this thesis, dataset development and application development are planned to extend over the next year, and the AI model development will be a key focus of my PhD over the coming four years.

Besides this, the focus of this thesis shifted throughout the process. Initially, the plan was to develop the AI model and begin data collection. However, due to the lack of publicly available datasets suitable for model training and the ongoing ethics committee approval process for the database development study, the research priorities had to be adjusted. As a result, the interview study was initiated first. Later, once funding for the application development was secured—scheduled to begin at the start of 2025—the focus shifted toward preparing for the app development alongside the interview study. These adjustments reflect the dynamic nature of the research process, ensuring that the project progresses efficiently despite external constraints.

Lastly, the trajectory of this thesis was influenced by the decision to continue within the SENSAI project as a PhD candidate. As this decision was made after the initial project phases had already commenced, it led to a shift in focus. Rather than concentrating primarily on developing a proof-

of-concept AI model, the scope broadened to encompass the project as a whole. Key priorities now included preparing for the development of a high-quality multimodal dataset, defining the functional and technical requirements of the AI-based APA tool, and taking on the role of product owner during the app development process. These strategic choices ensure that this thesis lays a solid foundation for both the continuation of the SENSAI project and the upcoming PhD trajectory.

1.5 Readers Guide

This thesis is structured into seven chapters, each contributing to a comprehensive exploration of the development and validation of the AI-based APA tool.

Chapter 1 introduces the research context. It outlines the problem definition, objectives, methodology and scope of this thesis. By doing so, it sets the stage for chapters to follow.

Chapter 2 provides the necessary technical and clinical background to understand the context of the research, including key concepts related to cancer pain, pain assessment, artificial intelligence in healthcare and design and development approaches.

Chapter 3 presents the first findings from the exploratory interview study with oncologists. This chapter offers valuable insights into the current experiences of both patients and clinicians regarding pain assessment, highlighting the challenges and limitations they encounter. Furthermore, it incorporates the mobile health Technology Acceptance Model (mTAM) to explore the factors influencing the acceptance and adoption of AI-based APA tools. By examining the perceived ease of use, usefulness, and other critical dimensions, this chapter ensures that the design of the AI model aligns with the needs and preferences of one key group of end-users – oncologists – supporting the development of the conceptual framework.

The next chapter, Chapter 4, outlines the conceptualisation process of the AI-based pain assessment tool, detailing its transition from an initial idea to a working concept. The focus is on defining the tool's functionalities, technical components, and intended user interactions. By the end of this chapter, a structured working concept of the tool is established, forming the foundation for its further development, described in the next two chapters.

Chapter 5 details the design and development process of the AI-based APA application. The goals of the development, the planning, design process and outcomes of the first two sprints are outlined.

Furthermore, Chapter 6 describes the process of creating a multimodal pain assessment database, which serves as the foundation for training and validating the AI model. Within the chapter, the database development study protocol is presented.

In Chapter 7, synthesises the main findings of this thesis and translates them into recommendations for further development of the APA tool. It also outlines keys directions for future research to support the effective implementation of AI-based pain assessment in oncology.

Each chapter builds upon the previous, offering a systematic approach to the development of the AI-based APA model.

2 Background

This chapter lays the clinical and technical foundation for the development of an AI-based automatic pain assessment (APA) model for cancer care. It first explores the multidimensional nature of cancer-related pain and the challenges associated with its assessment in clinical practice. It then introduces key concepts in artificial intelligence, with a focus on machine learning and human-centred AI approaches. The chapter concludes by presenting a structured development framework for healthcare AI systems and applying it to the context of APA, illustrating each design phase with examples relevant to cancer pain assessment. Together, these perspectives highlight the need for clinically meaningful, technically robust, and user-aligned AI solutions.

2.1 Clinical Background

2.1.1 Understanding Cancer-Related Pain

2.1.1.1 Definition of Pain

Pain is something we all experience, but it is often hard to put into words. This was thoughtfully put by A.W. Frank: *"We have plenty of words to describe specific pains: sharp, throbbing, piercing, burning, even dull. But these words do not describe the experience of pain. We lack terms to express what it means to live 'in' such pain. Unable to express pain, we come to believe there is nothing to say. Silenced, we become isolated in pain, and the isolation increases the pain. Like the sick feeling that comes with the recognition of yourself as ill, there is a pain attached to being in pain."* [36 (p. 29-30)].

Likewise, defining pain proves to be challenging, for clinicians as well as scientists. In the early days, pain was framed as a direct result of tissue damage, a purely physical phenomenon [37]. According to the early theories, such as the intensity theory, specificity theory, or pattern theory, pain could be seen as a simple, linear transmission of signals from the site of injury to the brain. However, neither of these theories could explain why similar injuries produced different pain experiences in different individuals or how psychological factors influence pain perception. In 1965, Melzack and Wall transformed this understanding by introducing the gate control theory of pain: the idea that pain is not simply a direct result of injury but is modulated by the brain through a "gate" in the spinal cord [38]. This theory acknowledged that psychological factors, such as emotional states, could influence the perception of pain. Almost thirty years later, Melzack expanded upon this theory with the neuromatrix theory [39, 40]. This theory proposed that pain is generated by the brain itself, with multiple brain regions, the "neurosignature" responsible for creating the pain experience, independent of peripheral injury. It recognised the role of non-physical factors, including emotions and past experiences, in shaping pain. Nevertheless, even this did not fully encompass all aspects of pain. The biopsychosocial model emerged as the most comprehensive explanation. This theory of pain suggests that pain arises from the complex interplay of biological, psychological, and social factors, and any theory that overlooks one or more of these elements fails to offer a complete explanation for an individual's pain experience [41].

Based on our current understanding of pain, the International Association for the Study of Pain (IASP) defines pain as *"an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such tissue damage"* [10 (p. 1977)]. This widely accepted definition highlights the subjectivity and multidimensional nature of pain, encompassing sensory-discriminative, emotional-affective, cognitive, and behavioural dimension [19, 40]. Together, these dimensions shape not just how pain is felt, but also how it is endured and expressed, see Figure 2 for an overview of factors that influence the pain perception and expression.

The sensory-discriminative dimension refers to the physical and perceptual characteristics of pain, so how pain is identified and localised in the body. Most commonly the pain arises from somatic nociception, where noxious stimuli activate pain receptors in the peripheral nervous system. Signals from the receptors travel along the nerve fibres via the spinal cord to the brain. Within the brain, the somatosensory cortex plays a key role in processing these signals, allowing individuals to identify the location, intensity, and type of pain (*e.g.* sharp, dull, burning, etc.) [42]. This process is often referred to as the 'pain pathway', see Figure 3. The unpleasant feeling that is experienced motivates behaviour of escape and avoidance and serves as an immediate alarm of harm. It commands attention and action to minimize injury.

The emotional-affective dimension reflects the feelings associated with pain, such as fear, distress, or sadness [43]. These emotions are largely influenced by the brain's limbic system [44, 45], which connects the sensory perception of pain with emotional responses. For instance, chronic pain often leads to heightened emotional suffering, amplifying the overall experience and making pain harder to manage.

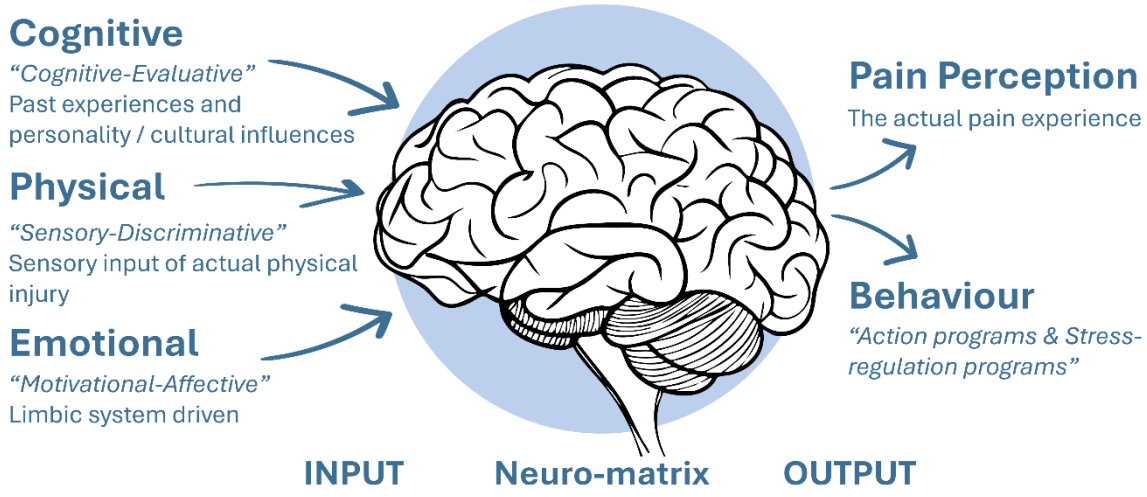

Figure 2 - Factors that contribute to the patterns of activity generated by the body-self neuromatrix, which comprises sensory, affective, and cognitive neuromodules. The output patterns from the neuromatrix produce the multiple dimensions of pain experience as well as concurrent homeostatic and behavioural responses. [Adapted from Melzack (2001) [40]]

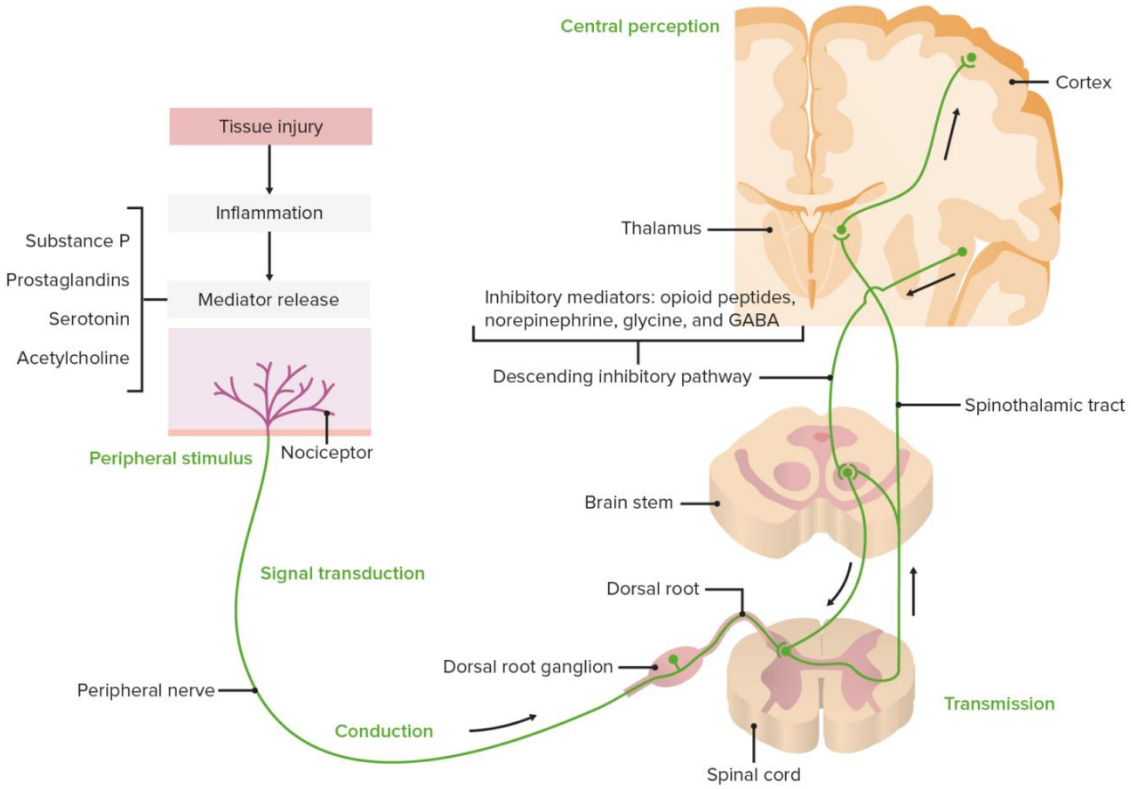

Figure 3 - Representation of the 'Pain Pathway': The nociceptors in the peripheral receptive field sense a pain stimulus. The signal travels through the nerve towards the spinal cord. The signal is transmitted to the spinothalamic tract that ends in the brain, where it is processed, resulting in central perception. [adapted from Lecturio Medical [46]]

The cognitive dimension encompasses the thoughts, beliefs, and interpretations surrounding pain [47]. This includes how an individual perceives their pain — whether they view it as manageable or overwhelming — and their expectations for relief or recovery. Cognitive factors, such as attention, coping mechanisms, and previous experiences, shape how pain is processed and can either amplify or mitigate the sensation.

Finally, the behavioural dimension, part of the outputs of the self-body neuro matrix model, involves the observable actions or reactions to pain. These may include verbal expressions (e.g., complaining or describing discomfort), physical responses (e.g., limping or guarding a painful area), or behavioural adaptations like avoiding activities. These behaviours often signal the presence and severity of pain, helping the individual prioritize escape, protection, or healing. However, they also influence and are influenced by the person's environment. For instance, the visible expression of pain can evoke support, empathy, or frustration from family, friends, or caregivers, shaping interpersonal dynamics. At the same time, societal or cultural norms regarding how pain should be expressed or endured may dictate how individuals outwardly respond to their discomfort. Through this interplay, pain extends its reach beyond the individual, impacting relationships and social roles.

2.1.1.2 Types of Pain

While the dimensions of pain provide a comprehensive understanding of how pain is experienced, it is equally important to recognize that pain itself can manifest in different forms. The type of pain a patient experiences can significantly influence how it is perceived and has to be managed and treated.

Pain can be classified in various ways, one of the most common distinctions being between acute and chronic pain. Acute pain typically has a sudden onset and lasts for less than three months, whereas chronic pain persists for longer than three months, either continuously or intermittently [48]. While this difference in duration may seem simple, acute and chronic pain are distinct clinical phenomena. Acute pain arises from a specific injury or disease, serving a protective biological function by alerting the body to potential harm. It is generally self-limited, meaning it resolves once the underlying cause heals. In contrast, chronic pain often extends beyond the expected healing time and may be considered a disease state on its own [49].

Another distinction could be made based on the pathophysiology of the pain. We could distinguish nociceptive, neuropathic and nociplastic pain. Nociceptive pain is the most common type of pain and is defined as "pain that arises from actual or threatened damage to non-neural tissue and is due to activation of nociceptors" [50]. This is often further divided as either somatic or visceral pain. Somatic pain originates in soft tissue and is due to stimulation of the peripheral nociceptors, as described in the previous section. Examples of causes of somatic pain are burns and wounds. Visceral pain is experienced due to damage of internal organs and tissues and is often described as dull and diffuse, and hard to localise. Examples of causes for visceral pain are tumour invasion, obstructions, or angina. Neuropathic pain is "pain caused by a lesion or disease of the somatosensory nervous system" [50]. It requires damage to peripheral or central nerves. Nociplastic pain is defined as "pain that arises from altered nociception despite no clear evidence

of actual or threatened tissue damage causing the activation of peripheral nociceptors or evidence for disease or lesion of the somatosensory system causing the pain" [50].

2.1.1.3 Cancer-related Pain

Cancer-related pain is defined as pain caused by the primary cancer itself or metastases or its treatment [51]. It is one of the most frequent and disabling symptoms of cancer, affecting a significant portion of patients. According to studies, approximately 30–50% of patients with cancer experience pain during treatment, with the prevalence increasing in those with advanced stages of the disease [13]. With the global prevalence of cancer on the rise and an increasing number of cancer survivors due to advancements in modern oncology, cancer-related pain has become an enduring concern for a growing population of patients.

The nature of cancer-related pain is particularly complex, as it can arise from a variety of sources. It may result from direct tumour invasion, pressure on surrounding tissues, or the side effects of cancer treatments such as surgery, chemotherapy, and radiation. Additionally, pain can be exacerbated by psychological and emotional factors, such as anxiety, depression, and the stress associated with cancer diagnosis and prognosis. Social factors, including the patient's support system and their ability to access effective healthcare, further contribute to the multifaceted experience of pain.

Cancer-related pain can often present as both acute and chronic pain. Acute pain may occur following surgery, chemotherapy, or radiation therapy, while chronic pain is typically associated with advanced or metastatic cancer. One of the most challenging aspects of cancer-related pain is the presence of breakthrough pain: a severe, sudden exacerbations of pain that occur even when background pain is being managed [52]. This type of pain is prevalent in approximately 70% of cancer patients [53]. It can significantly affect the patient's quality of life and requires prompt and effective management strategies.

2.1.2 Pain Assessment Methods

Accurate pain assessment is the cornerstone of effective pain management [5]. It is essential for tailoring treatment strategies, monitoring their effectiveness, and improving the overall quality of life for patients.

To perform a pain assessment, three interconnected stages must be addressed. First, the patient must communicate their pain experience. Second, the physician must interpret the input the patient gave. Third, this information must be integrated with clinical findings and contextual factors, such as the patient's medical history, emotional state, and social circumstances, to form a comprehensive understanding of the pain. Each stage of the assessment process can be done in various ways, combined leading to different pain assessment methods.

In clinical practice, mainly two approaches are employed to facilitate communication from the patient to the physician: self-reports, where patients directly describe their pain, and observation-based methods, where clinicians assess pain through behavioural and/or physiological indicators [54]. Regarding the interpretation of the input from the patient, this is normally based on the experience of the physician, the utilisation of validated pain assessment tools or scales to quantify

and qualify the reported pain [5], and the agreements within the hospital. However, this interpretation could only take place in combination with the interpretation of the context in which the patient provided his/her information. The information that is available and considered differs per situation and physician.

2.1.2.1 Communication – Self-report and Observations

The current clinical practice relies heavily on the ability of the patient to communicate their pain experience to the physician verbally. Self-report is considered the gold standard for this communication, as it offers the most direct method for patients to describe their pain experience [54]. Through self-report, patients are asked to articulate their pain. There are different approaches to this assessment. Some frequently used mnemonic tools to help assess the pain systematically are the WILDA-approach [5], the PQRST-method [55] and the SOCRATES-approach. All approaches aim to cover various aspects of pain, *i.e.* the intensity, location, duration, factors that exacerbate or relief, timing, and impact on life. Together this gives a fuller understanding of the pain experience and the patient's subjective experience of pain is prioritised. However, while self-report is valuable, it can be challenging for some patients to fully express their pain this way, particularly when the pain is complex or difficult to describe.

To aid in this communication, tools like quantitative self-report scales, such as the Visual Analogue Scale (VAS) [56] and the Numeric Rating Scale (NRS), are commonly used. These scales have been in use since the 1950s and are popular due to their simplicity, ease of use, and time efficiency in clinical settings. Patients are asked to rate their pain on a scale from 0 (no pain) to 10 (the worst pain imaginable), providing a numerical measure of pain intensity. In the case of the VAS, a visual representation is provided, see Figure 4. This could help patients to better understand and express their pain levels. Both VAS and NRS have been shown to be reliable and valid tools for assessing pain and are widely utilized in daily clinical practice [57].

Despite the value of qualitative and quantitative self-report, these methods have several shortcomings. For instance, these methods of evaluation are solely focussing on pain intensity and are subject to high variability in individual perceptions of pain [58]. Another significant challenge is recall bias – patients are often asked to assess their pain retrospectively rather than in the moment, which can lead to inaccuracies in their estimates [59]. Adding to that, it is shown that patients have tendencies to catastrophize or underreport their pain in order to provoke a more or less aggressive treatment [60]. Aside from these difficulties, the practical usability of self-report can also be limited due to the inability of the patient to communicate and express their pain

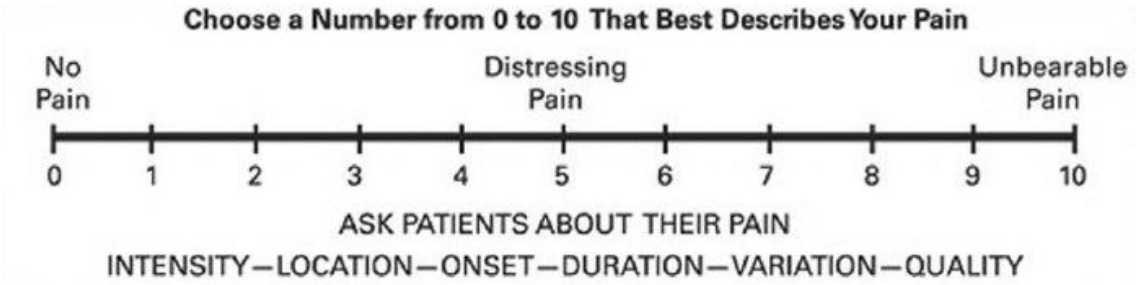

Figure 4 - Example of the frequently used Visual Analogue Scale (VAS) for pain assessment [79]

directly [61]. Groups of people for whom this can be a problem are infants, young children, elderly, people with a mental illness or cognitive impairments, patients who are sedated or heavily medicated, etcetera. What these groups have in common is that one or more of the requirements to communicate (approachability, consciousness, cognitive capability and mental stability) are underdeveloped or affected.

When self-report is not possible, observation-based pain assessment methods are typically employed. These observation-based pain assessments make, among others, use of the behavioural dimension of pain discussed in Section 2.1.1.1 and involve monitoring non-verbal and physiological responses that signal pain.

First of all, extensive research has shown that facial and vocal expressions are consistently associated with pain [62–64]. Vocal behavioural responses include among others moaning, crying and groaning [65], and increased pitch and loudness [66]. Facial expressions of pain also provide a powerful and often involuntary signal of distress [67]. They are considered among the most immediate and universal behavioural responses to pain, with specific facial action units reliably associated with painful experiences [68, 69]. Facial action units (AUs) represent the fundamental movements of individual facial muscles or muscle groups. Ekman and Friesen, in developing the Facial Action Coding System (FACS), analysed how these AUs correspond to facial expressions, proposing that each AU reflects a distinct, externally visible muscle movement [70]. AUs that have been found to relate to pain expression include among others brow lowering, orbital tightening, nose wrinkling, and upper lip raising [68]. The consistency of these expressions across individuals and populations has led to their use in clinical and research settings as indicators of acute pain.

In addition to facial and vocal expressions, observable physical behaviours provide critical cues for recognising pain. These include protective actions such as guarding, where an individual instinctively shields a painful area, and limping or shifting posture to reduce discomfort [71]. Such behaviours can serve both a defensive function - minimising further harm - and a communicative one, signalling distress to others [72]. Moreover, pain often prompts broader behavioural adaptations. Individuals may reduce their overall activity [73], withdraw socially, or avoid specific movements or contexts that might exacerbate their symptoms [74]. These actions reflect the motivational shift toward energy conservation and threat avoidance, adaptive in acute pain but potentially maladaptive when prolonged, as seen in chronic pain conditions [74].

Notably, these behaviours are shaped not only by internal pain mechanisms but also by social and environmental cues. For instance, people may suppress pain-related behaviours in clinical settings or in the presence of strangers due to perceived social threat or stigma [75], while expressing them more freely around trusted others [75, 76]. Understanding this dynamic interplay between pain, behaviour, and context is crucial for interpreting non-verbal indicators accurately.

Beyond behaviour, physiological responses also serve as valuable pain indicators. These include changes in heart rate, blood pressure, respiration, and skin conductance - autonomic signals that reflect the body's stress and arousal responses to pain [77].

Recognising both behavioural and physiological cues, several observation-based tools have been developed to assess pain in individuals unable to self-report. Some frequently used scales are the critical care pain observation tool [78], the non-verbal pain scale [79] and the behavioural pain scale [80]. These tools rely on third-party assessors - such as caregivers, family members, or healthcare professionals to - systematically evaluate patients' non-verbal and physiological indicators of pain. Nevertheless, with this approach, there are concerns about the intrinsic subjectivity and potential variability of outcome between the assessors with different background and levels of expertise [81].

2.1.2.2 Interpretation and Context

The interpretation of pain is inherently complex, as it involves not only the patient's self-reported pain but also how that pain fits within the broader context of the patient's medical condition. A patient's medical history can provide vital clues about the underlying cause of the pain. For example, a history of cancer or surgery may point toward pain caused by the tumour or post-operative complications. Similarly, a history of chronic illness such as diabetes or arthritis can help physicians differentiate between cancer-related pain and other types of pain that may be present concurrently. Understanding the medical context of pain helps the physician prioritise possible causes and select the most suitable treatments.

Psychological factors, including emotional distress, anxiety, or depression, also play a crucial role in pain perception. Psychological factors can amplify the sensation of pain or alter the patient's threshold for discomfort. As such, assessing the psychological state of the patient is essential for an accurate understanding of the pain experience and for tailoring treatment that addresses both physical and emotional aspects of pain.

In addition to psychological and medical factors, social circumstances such as family support, access to healthcare, and socioeconomic status can influence the pain experience and the effectiveness of pain management strategies. A lack of social support, for example, can lead to increased stress and feelings of helplessness, which may exacerbate pain. Similarly, patients with limited access to healthcare may experience untreated or undertreated pain due to financial constraints or logistical difficulties. By considering these social factors, physicians can better address the broader context in which pain occurs and provide more effective, patient-centred care.

When considering the pain and context information, not every physician will come to the same conclusion and will take the same measures. The interpretation of pain can also vary significantly depending on the physician's knowledge, experience, and familiarity with pain assessment tools [82]. Physicians with more experience in managing pain, particularly complex cases such as cancer-related pain, may be more adept at identifying subtle indicators or symptoms of pain that less experienced clinicians might overlook.

The use of standardized pain assessment tools, such as the VAS or NRS, can help provide a more consistent approach to interpreting the patient's pain. These tools help minimize subjective bias and allow healthcare providers to track pain over time and across clinical settings. However, while these scores are crucial for assessing pain intensity and tracking changes, they should not be used in isolation for clinical decision-making [83]. These scores should still be interpreted within the

context of the patient's overall condition and clinical history. To improve the usability of these scores, numerous efforts have been made to categorize pain based on intensity. One commonly used classification categorizes pain into three severity levels: mild (NRS 1–4), moderate (5–6), and severe (7–10) [84]. When combined with other clinical factors, these classifications help healthcare providers gain a more comprehensive understanding of the patient's pain experience.

Altogether, the interpretation of pain is not a one-size-fits-all process. It is shaped by the physician's individual experience and expertise, the use of standardized tools, and the institutional practices that guide pain assessment within different healthcare settings. By integrating these various components, physicians are better equipped to make an informed, accurate pain assessment that leads to optimal treatment outcomes for the patient.

2.1.2.3 Clinical Application

Pain assessment plays a central role in clinical practice, especially for cancer patients, where managing pain effectively is critical to improving quality of life. The integration of pain assessments into routine clinical care ensures that healthcare providers can make informed decisions about pain management, monitor treatment effectiveness, and adjust interventions accordingly [5].

Based on scientific and practical knowledge, the government, many hospitals and healthcare institutions have established clinical protocols for pain assessment, which may include guidelines on the frequency of assessments, the specific tools to be used, and the thresholds for escalating care. In the Netherlands, the *VMS-veiligheidsprogramma* [85] and the *IGJ Indicatoren, Basisset MSZ Verbeterdoelen en toezichtvragen* [86] provide practical frameworks and improvement goals for the timely recognition and treatment of pain, aiming to ensure that patients receive appropriate care in a structured and systematic manner. In the Erasmus Medical Centre guidelines have been made on the cancer-related pain management [87].

Pain assessments are typically performed at various points throughout the patient's care journey, with particular emphasis during initial consultations, at regular intervals throughout treatment, and whenever there is a significant change in the patient's condition. For cancer patients, pain assessments may occur daily in inpatient settings, where frequent monitoring is essential due to the acute nature of some cancer treatments and the severity of pain. For instance, protocols specify that pain should be assessed at least once per shift for hospitalized patients, with documentation of changes in pain levels and adjustments made to the treatment plan as needed. In outpatient settings, pain assessments may be conducted less frequently. Pain assessments are often conducted during every visit, with the results influencing decisions on medication adjustments or further interventions. While pain monitoring systems are not yet widely implemented in outpatient cancer care, this area is actively being researched, and the integration of more systematic pain monitoring tools is gaining increasing attention.

In clinical practice, pain assessments are generally carried out by a range of healthcare professionals, including oncologists, nurses, and pain specialists. In inpatient settings, nurses often play a key role in conducting regular pain assessments, typically using standardized tools such as the NRS or VAS to record the patient's pain intensity. Oncologists or other specialists

may also conduct assessments during patient visits and are responsible for interpreting the results in the context of the patient's overall condition. In outpatient settings, the responsibility for pain assessment often rests more with the oncologist or primary care provider, although the patient is expected to take a more active role in managing their pain. Patients are encouraged to be proactive in reporting significant changes in their pain status.

2.1.3 Impact of Pain Assessments on Clinical Decision-Making

The results of pain assessments play a critical role in clinical decision-making. For the oncologists in the Erasmus Medical Centre a guideline has been made [87]. This guideline emphasizes on understanding the cause of pain, treating the cause of the pain, treating the symptom of experiencing pain with analgesics (based on the type of pain), and consulting with other specialists. Additionally, it mentions the importance of regularly assessing pain intensity to monitor the pain experience and evaluate the pain management strategy. See Appendix A for the flowchart presented in the protocol.

For cancer patients, pain management follows the principles outlined in the World Health Organisation's (WHO) Analgesic Ladder, a framework for providing escalating pain relief based on the severity of the pain [88], see Figure 5. It provides suggestions for clinical decisions regarding when and what type of medications should be given to patients based on their severity of their pain as indicated by their self-report. Non-opioid analgesics are recommended for mild to moderate pain, and opioid analgesics are recommended for moderate to severe pain. This classification underscores the importance of self-reported pain scores in guiding treatment choices.

While the WHO ladder provides a valuable baseline, it does not account for the complexity of individual patients' experiences. For example, two patients reporting similar pain intensities may require different treatments based on their medical history, psychological state, or treatment goals.

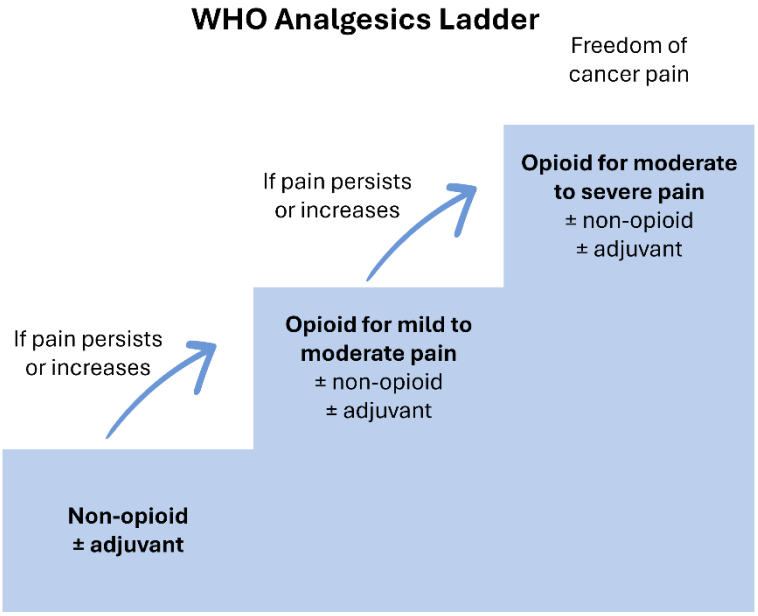

Figure 5 - Three-step Analgesic Ladder for Cancer Pain Relief, visualisation based on WHO guidelines for the pharmacological and radiotherapeutic management of cancer pain in adults and adolescents. Geneva: World Health Organisation; 2018. PubMed [85]

A holistic approach to pain assessment—one that incorporates not only self-reported pain scores but also contextual factors such as the patient's emotional, social, and physiological state—can lead to more personalized and effective pain management strategies [23].

Regular and systematic pain assessments are crucial for identifying fluctuations in pain levels, allowing timely adjustments to the treatment plan. For instance, patients experiencing breakthrough pain may require rapid escalation of analgesic therapy or additional interventions. Conversely, a sustained decrease in pain levels might indicate an opportunity to de-escalate treatment, reducing the risk of side effects and medication dependency.

Pain assessments also play a critical role in managing patients' expectations and fostering shared decision-making. By discussing pain scores and trends with patients, clinicians can align treatment goals with the patient's preferences and experiences, improving adherence and satisfaction with the care plan.

2.2 Technical Background

In the era of digitisation, the analysis of vast and complex datasets is becoming increasingly common in healthcare. Artificial Intelligence (AI) is playing a growing role in this process, demonstrating its potential to support clinicians, enhance diagnostic precision, and personalise treatment. In the context of pain management, AI offers promising opportunities to uncover deeper insights into the underlying mechanisms of pain and improve its assessment, and more specifically cancer-related pain.

However, the development of clinically useful AI systems is not solely a technical challenge. For these tools to be trusted, adopted, and integrated into everyday healthcare practice, they must also be designed with the end users in mind. This includes not only technical robustness, but also ethical responsibility, transparency, and usability for both clinicians and patients.

This section introduces the core concepts and methods behind AI and machine learning, with a specific focus on automatic pain assessment (APA) using facial expression and voice analysis. It also explores the design principles that guide the development of human-centred, user-friendly AI applications in clinical settings. By combining insights from data science, design thinking, and healthcare practice, this chapter aims to provide a comprehensive foundation for understanding the technology and design choices that underpin this thesis.

2.2.1 Artificial Intelligence: Key Concepts and Terminology

2.2.1.1 What is Artificial Intelligence?

Originally, the term ‘Artificial Intelligence’ was introduced by J. McCarthy in the 1950s and called it “the science and engineering of making intelligent machines” [89]. Initially, AI focused on enabling computers to recognise patterns with minimal human involvement. Early efforts in AI focused on rule-based systems that aimed to replicate human reasoning through explicit programming. Over the decades, the field has evolved significantly, driven by advances in

computing power, the availability of large datasets, and the development of statistical learning techniques.

Modern AI systems can perform tasks traditionally requiring human intelligence, such as prediction, classification, natural language processing, decision support, and generative modelling. In healthcare, these tasks translate into applications like diagnostic imaging analysis, triage and risk prediction, personalised treatment recommendations, and clinical documentation support.

In healthcare, AI is increasingly being used for tasks such as image analysis, diagnosis, treatment planning, and monitoring patient conditions [90]. Its ability to process large, complex datasets – commonly referred to as "Big Data" – allows AI systems to uncover patterns and make predictions that might be difficult for humans to detect unaided.

Importantly, the growing interest in AI coincides with the mounting pressure on healthcare systems worldwide to meet the so-called 'quadruple aim': improving population health, improving the patient experience of care, enhancing caregiver experience and reducing the rising costs of care [91, 92]. Because of ageing populations, the growing burden of chronic diseases – including cancer – and the rising costs of healthcare it is challenging for governments, payers, regulators and providers to achieve these aims [93]. The application of technology and AI has the potential to address some of these challenges and transform care [94].

In the context of this thesis, AI is explored for its ability to support the assessment of cancer-related pain through observable cues like facial expressions and vocal characteristics.

2.2.1.2 Machine Learning and Deep Learning

Two concepts related to AI are machine learning (ML) and deep learning (DL), see Figure 6.

ML is a subset of AI that enables systems to learn patterns from data and improve performance over time without being explicitly reprogrammed [95]. ML models rely on statistical methods to map relationships between inputs and outputs and are often categorised into three types:

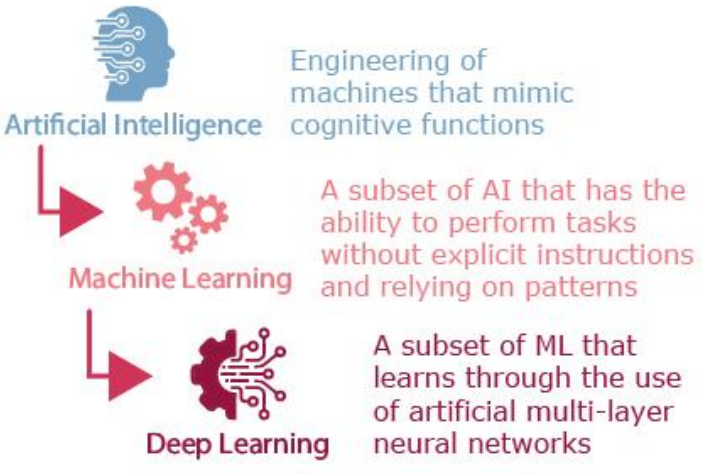

Figure 6 - Relation of AI Concepts

- Supervised learning uses labelled data to learn a mapping between input variables (e.g., a video recording of a patient) and output labels (e.g., a reported pain score). This is the most common approach in clinical AI research.
- Unsupervised learning explores unlabelled data to find hidden patterns, such as clustering patients with similar symptom trajectories.
- Reinforcement learning involves an agent learning to make decisions through feedback from its environment, useful for sequential decision-making problems.

For a step-by-step explanation of machine learning working mechanisms and development process, see Section 342.2.4.

DL is a specialised subfield of machine learning that draws inspiration from the structure and functioning of the human brain. At its core, deep learning involves artificial neural networks—layered computational models designed to automatically learn to extract meaningful patterns and develop its own representations from the raw data [96]. These networks are particularly powerful for processing high-dimensional, unstructured data such as images, video, and audio.

The working mechanism is inspired by the structure and function of neurons in the brain, see Figure 7. As shown in Figure 7a, a biological neuron receives signals through its dendrites, processes them in the cell body, and sends the resulting signal through the axon to other neurons via axon terminals. This simple but highly interconnected communication system forms the basis of how the brain processes information.

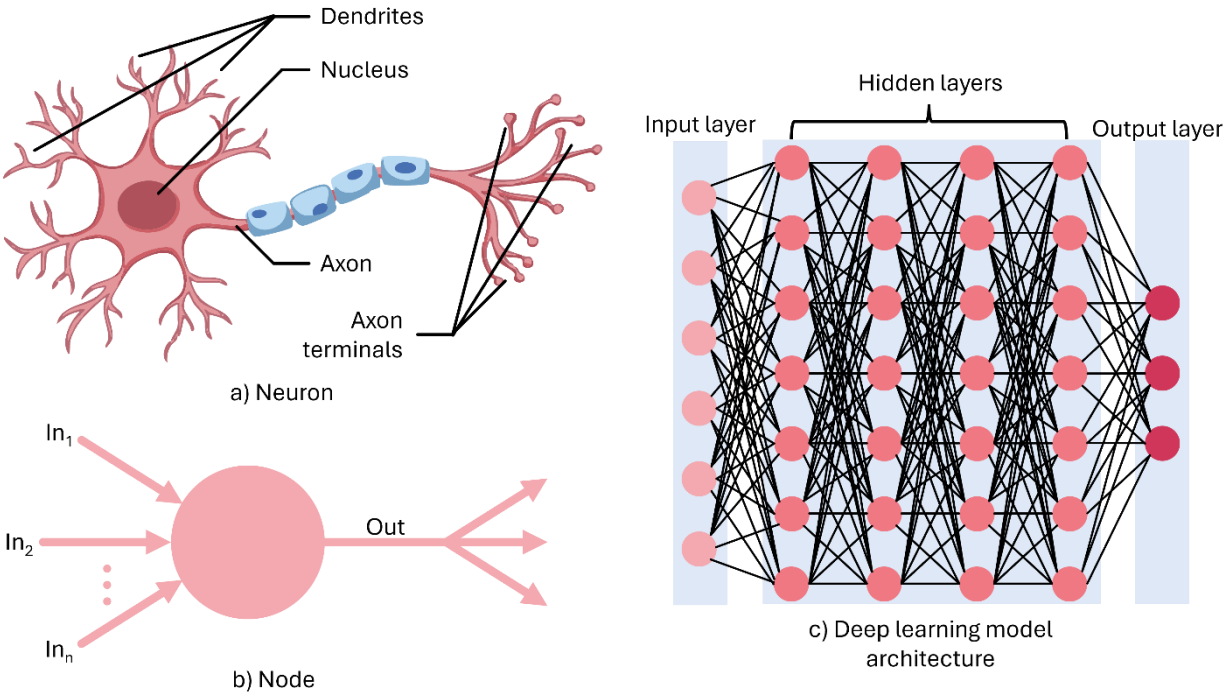

Figure 7 - Representation of the elements of deep learning: a) In the human body, a neuron receives signals at its dendrites, which then travel through the axon to the axon terminals. b) Similarly, in a deep learning network, nodes receive multiple inputs, process them, and pass the resulting output to the next layer of neurons. c) In the deep learning network, an input layer introduces the data. This data is processed through multiple hidden layers, where each node applies transformations before passing the results to the next layer. All information comes together in the output layer.

Artificial neural networks mimic this structure. As illustrated Figure 7b, a single artificial neuron – called a node – receives multiple input signals. These inputs are each assigned a weight, summed together, and then passed through a nonlinear activation function [97]. This transformation step is critical, as it enables the model to capture complex, non-linear relationships in the data. The output of this node is then sent forward to the next layer in the network.

Figure 7c depicts the full architecture of a deep learning model. It consists of an input layer, multiple hidden layers, and an output layer. Data enters the network through the input layer, which could consist of, for example, pixel values from an image or acoustic features from an audio recording. The information then flows through the hidden layers – a process known as forward propagation – where each layer transforms the data into increasingly abstract representations. As the data moves deeper into the network, it is progressively reshaped into features that are more relevant for the task at hand. Eventually, the output layer produces a prediction, such as a pain intensity score.

Training a deep neural network involves adjusting the weights associated with the connections between nodes. This is done through a process called backpropagation, where the error between the model's prediction and the actual label is calculated and used to update the weights, allowing the network to learn over time.

One of the most powerful aspects of deep learning is its ability to learn features directly from raw input data. Rather than requiring handcrafted features – which depend on human intuition – deep learning models can automatically discover useful patterns in the data. In the context of pain assessment, this means that a model could learn to recognise subtle muscle movements in the face or changes in vocal tone associated with discomfort, without needing explicit instructions on what to look for.

2.2.1.3 Human-Centred AI

Whereas ML and DL were described as *what* AI is and *how* it functions technically, the concept Human-Centred AI (HCAI) is a design philosophy and development approach that focusses on *how* AI could be developed and integrated into real-world contexts.

HCAI is an emerging field focused on designing AI systems that enhance and support human capabilities rather than replace them. Its goal is to re-position humans at the core of the AI lifecycle [98, 98, 99] and enhance human performance in ways that are reliable, safe, and trustworthy by augmenting – rather than replacing – human capabilities [100]. This approach prioritises human needs, values, expectations, and preferences over algorithmic optimisation, resulting in systems that are more accessible, transparent, and trustworthy [101]. This way it promotes the design of AI technologies that are not only technically robust but also usable, interpretable, and ethically aligned with the people they serve. In healthcare, this means creating systems that clinicians and patients can understand, control, and trust.

This approach involves developing comprehensive frameworks to guide the entire AI system lifecycle – from design and implementation to evaluation, operation, maintenance, and eventual decommissioning – with the aim of ensuring that technologies align with human values, safeguard

user safety, and preserve human autonomy [102]. HCAI recognises the importance of user diversity and seeks to accommodate differences in preferences, experiences, and contexts. It supports the coexistence of high levels of automation and meaningful human control [103] and encourages an iterative, participatory development process involving end-users at each stage.

By embedding human values into the AI development process, HCAI helps ensure that technologies are not only intelligent but also responsible and responsive to the realities of clinical practice. HCAI is beginning to make impacts on medicine [104], but widespread adaptation remains forthcoming.

2.2.2 Design-Centred Development of AI Systems

As the use of artificial intelligence in healthcare continues to grow, it becomes increasingly important to ensure that such systems are not only technically accurate but also meaningfully usable in clinical practice. This requires moving beyond model performance alone to consider how the technology is developed, implemented, and experienced by its users. Design-centred development approaches, including user-centred design (UCD) and structured design frameworks like the Double Diamond, offer practical tools and methodologies for achieving this. These approaches are highly compatible with the principles HCAI.

2.2.2.1 User-Centred Design in Health Tech

Health technologies are designed to support health behaviour change and / or the management of illness [105]. However, their effectiveness depends not only on technical performance but also on whether intended users – such as patients and clinicians – find them usable and useful in practice. Usability refers to the degree to which a system can be safely, effectively, and efficiently learned and used [106].

UCD is an approach that incorporates user-focused activities throughout the entire development process [107]. It allows end-users to influence how a design takes shape, ensuring that the resulting system better aligns with their needs and preferences [108]. UCD methods include identifying and understanding the user population, analysing user tasks and requirements, testing prototypes, evaluating design alternatives, resolving usability issues, and iteratively refining features and interfaces based on user feedback. By engaging users throughout the development cycle—often through interviews, observations, prototypes, and usability testing—designers can build systems that are more likely to be accepted, trusted, and effectively adopted in practice.

Once considered time-consuming or dispensable, the benefits of UCD are now well established [33, 109]. Research has shown that involving users during the development of a new system improves the accuracy of user requirements, increases acceptance, and enhances system quality [110]. In addition, early identification and resolution of usability issues can substantially reduce development time and costs [111]. In the context of health technologies, UCD has been found to improve usability and functionality, thereby increasing the likelihood of promoting the intended health behaviours and achieving better health outcomes [109].

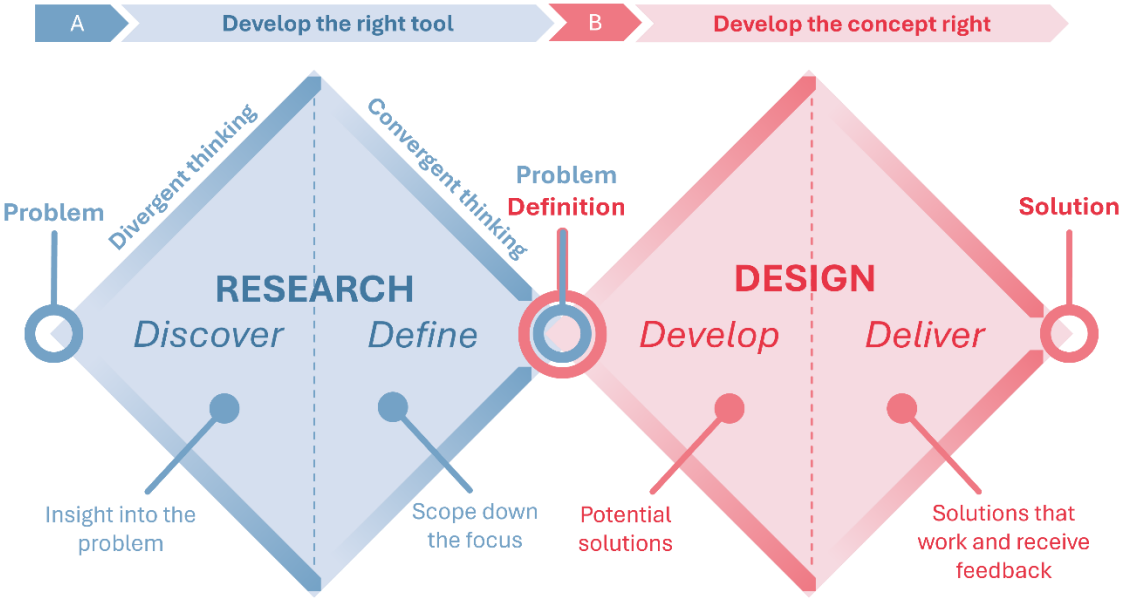

Figure 8 - The Double Diamond model

2.2.2.2 The Double Diamond Framework

A commonly used structure to guide design processes like UCD is the Double Diamond framework, developed by the British Design Council [34]. This model relies on the interplay between divergent and convergent thinking and breaks the design process into four distinct stages: discover, define, develop, and deliver (see Figure 8).

The first diamond consists of the Discover and Define phases. During Discover, designers explore the problem space openly, engaging users, reviewing literature, and identifying needs. In the Define phase, the insights gathered are synthesised to clearly articulate the problem to be solved. The second diamond includes the Develop and Deliver phases. In Develop, solutions are ideated and prototyped, often in collaboration with stakeholders. Deliver involves testing, refining, and implementing the final product.

This framework supports iterative development and accommodates uncertainty – two characteristics that are especially relevant in complex, dynamic fields like healthcare. In the context of AI, the Double Diamond can be used to structure the development of clinical tools [112], ensuring that technical design decisions are always grounded in real-world needs and constraints.

2.2.2.3 Integration with HCAI

Design-centred methods such as UCD and the Double Diamond framework naturally align with the principles of Human-Centred AI. Both emphasise the importance of human control, usability, safety, and ethical alignment throughout the AI lifecycle.

By actively involving end-users in the discovery, design, and evaluation of AI systems, these approaches help ensure that technologies are not only effective but also meaningful and trusted in their intended contexts. Furthermore, design-centred development supports key HCAI goals such as transparency, fairness, and interpretability, especially when complex or opaque AI models are used.

In summary, integrating structured design methods into the development of AI systems is not merely a matter of improving usability—it is a fundamental step toward responsible, human-aligned AI. In the case of automatic pain assessment (APA), such approaches are particularly valuable given the sensitive, subjective, and deeply personal nature of pain.

2.2.3 AI for Pain Assessment

As outlined in Sections 2.1.1.1 and 2.1.2.1, pain is a multidimensional experience that includes behavioural expressions such as facial movements, vocalisations, posture adjustments, and activity avoidance, alongside physiological responses like elevated heart rate or blood pressure. While these expressions have traditionally been assessed through observation-based tools, such assessments are inherently subjective and prone to inter-rater variability [113]. In this context, AI offers a promising solution to support and potentially augment pain assessment practices, by automatically detecting and interpreting pain-related behaviours and physiological signals.

2.2.3.1 Overview of APA research

APA systems use ML to recognise patterns in in observable behaviours and physiological data, allowing for objective estimation of pain intensity or presence. To achieve this, AI models are trained on different types of input data, also referred to as modalities. The data reflects different dimensions of pain expression. Systematic reviews have found that these commonly include vision/video, audio, and physiological signals [114–117]. Each of these modalities provides unique insights into a patient's pain experience:

- Vision/Video Modality: Video recordings are used to capture facial expressions, body posture, and protective behaviours. In particular, facial AUs, such as brow lowering or orbital tightening [68], have been consistently linked to pain and are frequently used in APA systems to infer pain presence and intensity.
- Audio Modality: Audio recordings are used to capture vocal expressions such as moaning, groaning, or variations in pitch and loudness are informative pain cues [65, 66], especially in situations where visual data is unavailable.
- Physiological Signals: Heart rate variability, skin conductance, and respiration patterns offer objective insights into the autonomic response to pain [77]. These signals are typically collected through sensors or wearable devices and are especially valuable in unconscious or non-verbal patients.

One key advantage of these modalities is that they can all be captured non-invasively. Facial expressions can be recorded via video; vocalisations can be analysed through ambient microphones; and physiological parameters can be obtained through external sensors or wearables. This non-invasive nature makes APA particularly well-suited for real-world clinical applications, including remote or outpatient settings. It also lowers the threshold for repeated measurements and improves patient comfort – factors that are especially important in sensitive contexts such as oncology and palliative care.

While each modality individually captures important aspects of pain, the integration of multiple modalities – known as multimodal modelling – is increasingly recognised as the most robust

approach [115]. Multimodal APA models combine complementary information across modalities, improving predictive accuracy and model generalisability.

While research has explored all three modalities independently and in combination, the non-invasive nature of these inputs makes them particularly attractive for use in clinical practice. Among these, audio and video data were considered especially promising due to their ease of collection (with commonly used smartphones) and alignment with current clinical communication. As explained in Chapter 4 (Section 4.3.1.2), this study focuses on audiovisual input for these reasons and due to their proven feasibility and performance in prior APA research.

In my previously performed literature study (see additional provided document), I reviewed recent developments in APA models using facial expression and voice analysis. The majority of early research focused on unimodal models - primarily vision-based - that either used raw visual input (e.g. video frames of facial expressions) or relied on intermediate representations such as facial AUs. These models employed various machine learning approaches, from traditional classifiers to deep learning architectures, and explored both static and dynamic features to capture temporal patterns of pain expression. In parallel, audio-based models analysed features like pitch, prosody, and breathiness to classify or regress pain intensity, albeit with less popularity than their visual counterparts.

Only four studies had been identified that have successfully implemented multimodal APA models combining facial and vocal input [118–121]. While these pioneering efforts demonstrate the potential of hybrid models to enhance pain assessment, their limited number made it difficult to draw definitive conclusions about the effectiveness of specific modality combinations or fusion strategies.

2.2.3.2 Benefits and Challenges of AI in Pain Management

AI-enabled pain assessment systems might offer several key advantages over traditional, clinically used methods:

- Objectivity: By quantifying behavioural and physiological indicators, AI can reduce subjective bias and inter-observer variability.
- Automation: Continuous monitoring and analysis of pain-related cues can assist in detecting underreported or unnoticed pain episodes, particularly in non-verbal or critically ill patients.
- Personalisation: AI models can adapt to individual expression patterns over time, potentially enabling more tailored and accurate pain management.

However, important limitations and ethical concerns, identified in the earlier performed literature study, must also be acknowledged. Dataset limitations hinder progress. High-quality, labelled datasets of real patient pain expressions - especially in oncology - are scarce due to privacy concerns and practical constraints in data collection. As a result, many APA models are trained on small, homogeneous datasets, which may not generalise well to broader clinical populations.

Furthermore, ethical and implementation issues persist. These include concerns about patient privacy, algorithmic bias, explainability, and integration into existing clinical workflows. Ensuring

that AI systems are interpretable and trustworthy to both clinicians and patients is essential for their acceptance and adoption.

In sum, AI-based APA tools represent an innovative and promising frontier in pain medicine, particularly in complex settings like oncology. By aligning advances in machine learning with insights from behavioural science and clinical needs, these systems have the potential to improve pain recognition, facilitate timely intervention, and support more personalised patient care.

2.2.4 Development Process of the AI-based APA Model

The design, development, and implementation of HCAI models for healthcare must follow a thoughtful, multi-phase approach that centres on clinical relevance, model performance, and real-world usability. An often-cited approach for healthcare models was published by Chen, Liu and Peng [35] and serves as guiding in the development process. Their approach consists of six phases: 1) problem selection, 2) data collection, 3) ML model development, 4) validation, 5) assessment of impact and 6) deployment and monitoring, see Figure 9.

This section outlines each of these phases and relates them to examples in AI-based APA development.

2.2.4.1 Phase 1 – Problem Selection

When designing an AI model in the healthcare field, first the following questions must be answered: "What is the purpose of designing this learning model?". To answer this question the problem and challenges in the healthcare field must be identified. In addition, the existing solutions presented in the area so far should be considered [122]. Based on this analysis, a clear

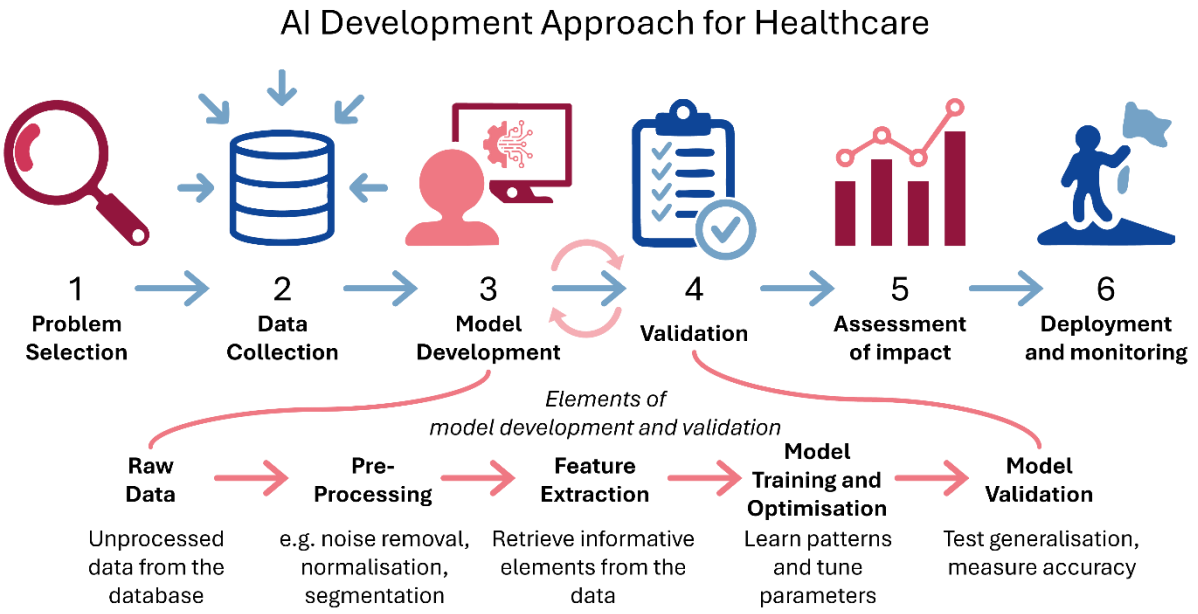

Figure 9 - The six-phase approach of developing an ML model for healthcare implementations [based on the approach described by [121]. The development of machine learning models in healthcare follows a six-phase process: (1) selecting a relevant and impactful problem, (2) collecting appropriate data, (3) developing the model, (4) validating performance, (5) assessing clinical impact, and (6) deploying and monitoring the model in real-world settings. Phases 3 and 4 contain the core machine learning pipeline, which includes processing raw data, extracting relevant features, training and optimizing the model, and evaluating its generalizability on unseen data.

problem definition can be formulated, and an appropriate learning task for the model can be determined. The learning task defines what the model should achieve, whether it involves classification, regression, anomaly detection, or another approach, based on the specific needs of the healthcare application. This learning task will determine the further designing process of the model.

Example: In AI-based APA, the goal could be improving the accuracy and objectivity of pain evaluation for cancer patients. Based on this, the learning task could involve pain intensity classification, where the model analyses multimodal data (e.g., facial expressions and vocal characteristics) to predict pain levels on a predefined scale.

2.2.4.2 Phase 2 – Data Collection

AI models in healthcare rely heavily on data to make accurate predictions. Two key points in the first stages of designing a model are deciding on the required type of data and reviewing data availability. The former involves defining the specific characteristics of the data needed, such as the modality and its format. The latter implies that as a researcher you must be mindful of existing data sources, as adequate data availability is essential for both developing and evaluating the learning model. In healthcare, data scarcity can arise from factors such as limited digital records, patient privacy concerns, commercial restrictions, or the rarity of certain diseases. Therefore, it could be necessary to collect new data and develop a new dataset. However, if relevant data is already available, it is important to avoid generating excessive new data, as this could place an unnecessary burden on both patients and the healthcare system.

Example: To create a valuable database to develop a model that could predict the pain level from facial expressions and vocal cues, lots of images or videos from people's faces and audio recordings from people's voices while expressing a certain pain level have to be collected. The pain level has to be labelled to the data. Besides this demographic data could be labelled to these datapoints to be able to describe the participant. All data has to be saved using a certain structure to create a dataset.

2.2.4.3 Phase 3 – Model development

After the data is collected, the development of the actual ML model could be started. For this the quality of the data, type of learning scheme, and the learning task must be considered.

First it is essential to prepare the data, as a machine learning model relies on high-quality data for effective training and optimal performance. Achieving this is one of the most challenging parts. In general, pre-processing enhances data quality before the learning model is created. What has to be done depends on the data, the type of model and the goal, but this may involve filtering outliers, normalising, or resampling outliers. It might also involve annotating the data, *i.e.* adding labels to identify specific elements, to make it suitable for training.

Once the data has been prepared, the next step is to develop the machine learning model. First features can be extracted. During feature extraction relevant patterns or characteristics are derived from raw data. Features refer to the key attributes or patterns that AI models use to make predictions. The goal of this process is to preserve the information from the original data

while improving model performance compared to using the raw data alone. In APA, these may include facial muscle movements or vocal properties. Toolkits, like OpenFace [123] and OpenSMILE [124], which extract a predefined set of features based on already trained models, can support this process. When a lot of features are extracted, it could be expected that not all are equally informative. Feature selection, in which dimensionality is reduced by identifying the most informative features for the learning task, helps improving efficiency and performance. Next, model training and optimisation involves teaching the model to recognise patterns and relationships within the data. During this process, the model iteratively adjusts its internal parameters to minimise prediction errors. Supervised learning is typically used in APA, where the model learns to associate input features with known pain intensity labels (e.g. NRS scores). Hyperparameter tuning is conducted to improve performance, often guided by feedback from a validation set. This step is crucial to balance model complexity, ensuring the model is expressive enough to capture relevant patterns without overfitting to the training data.

Example: During the data-preparation phase, all the faces of patients could be cropped from the images and video recordings, and audio recordings could be segmented. It may also be necessary to synchronise the data input streams, i.e. audio and video recordings. Using these inputs, an algorithm could extract features such as facial muscle movements and vocal tone or pitch. However, not all features contribute equally to model performance, so selecting the most relevant ones is essential to prevent unnecessary complexity and overfitting. The selected features would then be used to train a classifier — a supervised learning model that categorises the input into discrete pain intensity levels. Labels such as NRS scores guide the learning process. During training, the classifier iteratively adjusts its parameters to minimise prediction error and can be fine-tuned using validation data to improve generalisability.

2.2.4.4 Phase 4 – Validation

Once the model has been trained and optimised, its performance must be assessed on unseen data to evaluate how well it generalises beyond the training environment. This is done using a test dataset that was not used during training or parameter tuning. The goal of this validation phase is to ensure that the model performs reliably in real-world scenarios, providing an unbiased estimate of its accuracy and robustness.

A central challenge in this phase is managing the balance between overfitting and underfitting. Overfitting occurs when a model learns the training data too precisely — including noise or random fluctuations — and fails to perform well on new data. Underfitting, in contrast, reflects a model that is too simplistic to capture the underlying patterns in the data. A well-generalising model strikes a balance between these two extremes.

To improve generalisability and mitigate overfitting, cross-validation (CV) techniques are commonly employed during model development. In k-fold CV, the dataset is divided into k equal parts, and the model is trained and tested k times, each time using a different fold for testing. In leave-one-subject-out CV, the model is iteratively tested on each individual while being trained on all remaining subjects – a method particularly suitable for person-dependent data, such as pain expressions.

Example: Consider a classifier trained to assess a patient's pain level based on facial and vocal cues. During training, it learns to associate specific patterns (e.g., brow lowering or increased vocal pitch) with pain intensity levels. In the validation phase, the model is tested on unseen recordings from different individuals. Performance metrics such as accuracy, recall, or area under the ROC curve indicate how well the classifier generalises. Ideally, this evaluation would

2.2.4.5 Phase 5 – Assessment of Impact

After validating the model's performance, it is essential to evaluate its potential clinical utility. A performant model alone does not guarantee improvement in patient care — it must be assessed for its real-world relevance, usability, and added value in clinical workflows. This phase involves both technical and human-centred evaluations, including whether the model improves decision-making, integrates into existing routines, and is accepted by its users.

Importantly, no model is perfect, and it must remain clinically useful even in the presence of errors. Therefore, impact assessment also explores how clinicians interact with the model, how its predictions are used (or ignored), and how it compares to existing standards of care.

Example: Suppose the APA classifier achieves strong validation metrics in lab settings. During impact assessment, a clinical pilot is initiated where oncologists view the model's pain predictions alongside patient self-reports. Researchers assess how this influences their decisions, whether it improves alignment with patient experiences, and whether the tool is perceived as trustworthy and usable. Insights from this phase help determine if, and how, the model adds value in daily care.

2.2.4.6 Phase 6 – Employment and Monitoring

Once a model has demonstrated both performance and impact, it can be deployed into clinical practice. However, this is not the end of the development process — successful deployment requires continuous monitoring, ongoing feedback, and possibly retraining the model over time.

During this phase, developers and clinical teams must address practical challenges such as integration into electronic medical records, user interface design, data privacy, and regulatory approval. Additionally, model predictions must remain accurate and fair as new patient data becomes available, which calls for post-deployment monitoring and mechanisms to detect performance drift.

Feedback loops with users (e.g. patients and clinicians) are valuable here. These loops enable the system to be updated, adapted to different populations or settings, and maintained over time. This is especially important in healthcare, where changing practices, technologies, or population characteristics can influence model performance.

2.3 Bridging Clinical and Technical Perspectives

The assessment and management of cancer-related pain is a deeply complex clinical task, influenced by the subjective, multidimensional nature of pain and the limitations of current assessment methods. As this chapter has outlined, AI – particularly ML – offers promising opportunities to support pain assessment by analysing behavioural cues such as facial expressions

and vocalisations. Yet, the development of clinically valuable AI models requires more than technical accuracy; it must be grounded in the realities of clinical practice and guided by the needs of its intended users. A human-centred, design-informed approach ensures that AI tools are not only performant but also usable, interpretable, and ethically aligned with the people they aim to support.

3 Exploratory Interview Study

This chapter presents the exploratory study that forms the foundation for understanding the perspectives of both cancer patients and oncologists on pain assessment and their considerations regarding the use of an AI-based APA tool. It outlines the design and objectives of the interviews conducted, including questions about pain description, interpretation, and the potential use of AI for pain assessment. Through the analysis of these interviews, the chapter highlights the challenges faced by both patients and physicians in accurately assessing and communicating cancer pain. These insights provide valuable context for the development of an AI-based APA tool, guiding the research methodology and informing the next steps of the project.

3.1 Introduction

Cancer-related pain is a significant and distressing symptom that remains prevalent, even with the availability of effective treatments [125]. One of the main reasons for this ongoing challenge to effectively assess and manage pain is the complex and multifaceted nature of pain and the limitations of current assessment methods to fully capture this [63]. Beyond these intrinsic challenges, several barriers to effective cancer pain management have been identified [11, 126]. Among the patient-related barriers are beliefs and attitudes, such as a sense of inevitability about the progression of cancer or negative perceptions of opioid use, both of which can adversely affect

pain management [127]. On the professional side, barriers include knowledge gaps regarding pain management, inadequate pain assessment, and suboptimal prescribing of analgesics [128]. Furthermore, healthcare system related barriers include delayed access to care and appropriate analgesics [11].

In an effort to address these barriers and improve communication and assessment of cancer pain, there has been growing interest in the application of new technologies [129]. Several facilitators already support this development, such as the increasing digital literacy and programs for that in the EU [130, 131], the growing availability of connected devices [132], and a supportive policy environment encouraging digital health integration [133]. Digital health innovations, such as smart devices, wearable sensors, mobile health applications, telemedicine platforms, AI-driven decision support tools, have revolutionized how healthcare is delivered and accessed. These technologies, for example, enable remote monitoring, streamline clinical workflows, and assist in medical decision-making. As the development of health technology accelerates [134], their potential to transform the healthcare landscape continues to expand. In the context of pain assessment, this potential is reflected in the growing number of technological tools currently available or in development, and the ongoing research dedicated to advancing this area [135]. Despite these advancements, however, many digital health tools struggle to attract attention and sustain long-term use in clinical practice [135]. This is not always due to technical shortcomings, but often because they fail to meet the real-world needs of patients and healthcare providers. For example, in the systematic review of Allsop et al. [136] 24 studies on digital systems for cancer pain management were identified. The design processes of these interventions were often inadequate, failing to incorporate the perspectives of potential end-users. None of these systems were successfully implemented into clinical practice.

Due to research insights like these, there is a growing recognition of the importance of user-centred design in the development approach in digital health. Traditionally, healthcare technologies followed a top-down model, with engineers and developers driving innovation [137]. The perspectives of end-users often went unconsidered [138]. This lack of involvement from end-users, especially in terms of technology acceptance, is problematic, as it can increase the risk of a technology being rejected or abandoned after implementation, defeating its development purpose. Currently the development approach of such technologies is shifting towards a development process in which design with the user and understanding the existing environment are emphasised [139]. Being familiar with current processes and challenges and exploring end-user attitudes towards, for example, technology acceptance could greatly inform design work [140] and increase the changes of acceptance of the digital health technology [141].

In this project, an AI-based automatic pain assessment (APA) model is developed for cancer patients. The initial idea is to integrate the AI model into a mobile application patients could use for the APA. In order to develop a tool that will not only be technologically robust, but also have clinical value and sustained use, the modern principles of digital design are implemented in the design process early on. Despite knowledge about current pain assessment processes and potential barriers to optimal cancer pain management, there is currently no coherent explanatory framework to describe how patients and professionals approach cancer pain management, and what

influences the actions that they take to overcome the experienced barriers. Likewise, there is little known about the attitudes of the end-users towards this technology.

To address these gaps, this exploratory study used semi-structured interviews to examine the challenges cancer patients face in expressing pain and the difficulties oncologists encounter in assessing and managing it. The primary objective was to identify these challenges, while secondary objectives include exploring patient and oncologist views on potential solutions, evaluating their perspectives on AI-assisted pain assessment, and identifying the prerequisites for adopting the AI tool. Thematic analysis was conducted to capture the patterns and themes within participants' responses, providing a rich understanding of the pain assessment process and challenges. For the evaluation of technology acceptance, the methodology was informed by the constructs of the mobile health Technology Acceptance Model (mTAM). The insights from this study will serve as a foundation for refining the problem definition, developing the initial concept, and informing the design and functional requirements of the AI-based tool. This will help ensure that the tool is user-centred, clinically relevant, and effectively addressing the key pain management challenges experienced by both patients and healthcare providers.

The current report on this study presents the findings from the interviews conducted with oncologists. As the study is ongoing, interviews with patients have not yet been conducted to the point of saturation and have not yet been analysed; therefore, they are not included in this report.

3.2 Background

3.2.1 Exploratory Research

Exploratory research is an open-ended and flexible approach used to investigate areas where knowledge is limited or to gain new insights into complex phenomena. Unlike confirmatory research, which tests specific hypotheses, exploratory studies seek to identify patterns, generate hypotheses, and lay the groundwork for future investigations [142, 143].

Qualitative research methods are often employed in exploratory research due to their capacity to capture rich, detailed data. These methods include in-depth interviews, focus groups, and participant observation, which allow researchers to explore participants' experiences, beliefs, and behaviours [142]. Among these, in-depth interviews are particularly effective in uncovering personal perspectives, providing opportunities to delve into the reasoning, emotions, and contexts underlying participants' responses.

Semi-structured interviews are a widely used tool in qualitative exploratory research. They blend the structure of a predefined question guide with the flexibility to explore unexpected or particularly interesting responses. This adaptability makes semi-structured interviews well-suited for investigating complex issues, as they allow for comprehensive exploration while ensuring that key areas of interest are addressed [142].

3.2.2 Theory-Driven Qualitative Research

Theory-driven, or directed, qualitative research integrates theoretical frameworks into the research process to guide the collection, analysis, and interpretation of data. This approach ensures that findings are not only empirically grounded but also analytically robust and aligned with broader conceptual models [144]. By applying established theories, researchers can generate insights that extend beyond individual cases, linking qualitative findings to larger patterns or frameworks. Theoretical frameworks that are relevant to the performed study are further described in the next subsections.

3.2.2.1 Theory Acceptance Model

The adoption of new technologies, such as mobile health applications for pain management, is influenced by users' perceptions and attitudes toward the technology. To understand these attitudes and predict whether users will adopt and effectively use such technologies, the Technology Acceptance Model (TAM) provides a valuable theoretical framework. TAM was introduced by Davis in 1985 to predict and explain how individuals come to accept and use technology [145]. Currently it is one of the most widely used and influential theories in the field of information systems [146].

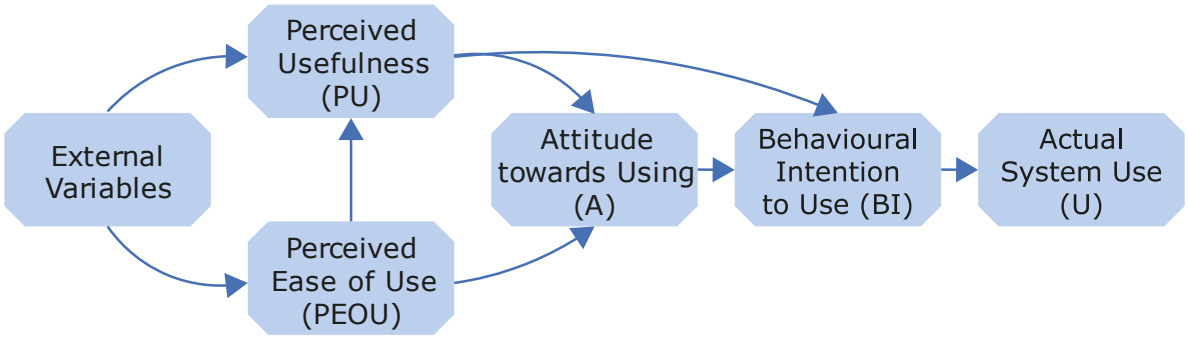

Figure 10 - The original Technology Acceptance Model [146]

The actual use (U) of a system or technology is the endpoint of the model. The factor that leads to U is the behavioural intention (BI) to use, defined as a person's subjective probability that he/she will use the system or technology [147]. The model suggests that BI can be assessed through a user's attitude (A) towards using the technology [145]. Two main attitude predictors have been proposed: perceived usefulness and perceived ease of use [145, 148]. Perceived usefulness (PU) is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance", while perceived ease of use (PEOU) refers to "the degree to which a person believes that using a particular system would be free from effort" [148 (p. 320)]. So, both factors influence A, which in turn shapes BI and the final U, see Figure 10. The theory suggests that if users find a technology to be both useful and easy to use, they are more likely to adopt it, leading to its successful integration and continued use.

Besides these relations, PEOU is considered to influence PU, because if a system is easy to use, users are more likely to see it as useful [149]. Moreover, beyond its impact on A, PU also directly influences BI, as users who perceive a technology as useful are more likely to intend to use it, regardless of other factors. In turn, external variables, such as social influence, could affect PU and PEOU and therefore indirectly influence A and U.

Over the years, the TAM has been extended and refined, with several revisions and new versions addressing various factors that impact technology acceptance [150, 151]. Those revisions and new models, like the Unified Theory of Acceptance and Use of Technology [152], have incorporated additional constructs such as social influence or subjective norm [150] and facilitating factors [152]. They try to capture the complexities of technology adoption more accurately. Other versions of the TAM have been developed to better suit the acceptance of technology in a specific field, such as healthcare or even mobile health [153].

3.2.2.2 Mobile Health Technology Acceptance Model

The relationship between TAM constructs and technology acceptance becomes more complex in healthcare settings. For instance, disease severity may have opposing effects on key factors: it can positively influence PU, as individuals with more serious conditions may see a form of health technology as valuable tools for managing their health. However, PEOU may decrease with disease severity, as patients experiencing greater physical or cognitive burden might find it more difficult to engage with new technologies. Moreover, research suggests that those who are more unwell may actually be less likely to adopt those technologies [154], a phenomenon partially explained by the "Healthy User Effect" [154, 155]. This effect describes how healthier individuals tend to be more proactive about their health and more inclined to engage with health-promoting technologies. As a result, the traditional predictive power of PU in the context of health technology may be less straightforward than in other settings.

Numerous studies have tried to capture these complexities in a technology acceptance model for the specific domain of healthcare. A large part focussed on finding a model suited for mobile health (mHealth) applications [156–160]. The World Health Organisation defined mHealth as "medical or public health practice that is delivered with support of mobile phones, patient monitoring devices, and other wireless devices" [161], a definition that will include the developed AI-based APA tool while used on the mobile phone of the patient. A study of Schnall et al. [162] introduced the mHealth TAM (mTAM), building on the traditional TAM framework. While the core TAM constructs remain central, mTAM incorporates additional factors to better capture the unique challenges of mHealth adoption. Specifically, perceived risk and trust play crucial roles in user acceptance of mHealth technologies. Perceived Risk (PR) refers to the users' subjective evaluation of incurring losses while using a technology [163]. Where PR could negatively affect BI, while trust could positively affect BI, see Figure 11. Trust (T) could be defined as the willingness of a user to be vulnerable to the actions of a technology based on the expectations that the technology will perform a particular action important to the trustor, irrespective of the ability to monitor or control that technology [164]. Trust becomes particularly important when

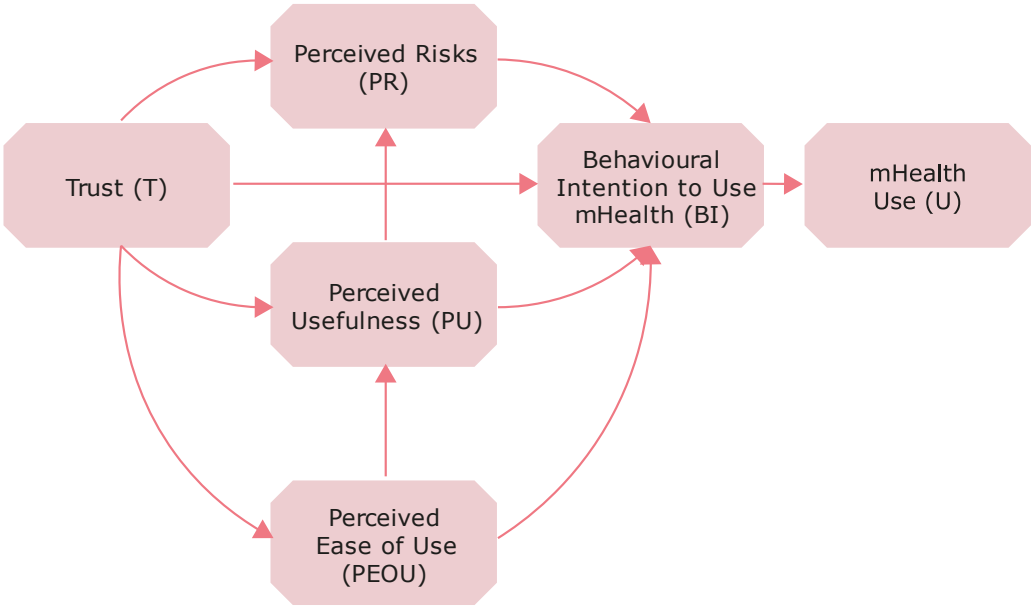

Figure 11 - Mobile Health Technology Acceptance Model [161]

uncertainty is high – such as when it is unclear where user information is stored or how it is tracked.

Despite these advancements, there is no consensus on which TAM adaptation best explains mHealth technology acceptance [165]. Nevertheless, in the preprint of a recent systematic review [166] the validity of TAM for mHealth applications was reaffirmed. Based on the 14 included studies it was demonstrated that PU and PEOU significantly influence behavioural intention to use MHAs. Besides this the review identified several key themes influencing mHealth along the constructs of the traditional TAM. These key themes included health risk perception, application factors, social factors, digital literacy and trust.

For pain assessment technologies, these findings highlight the importance of addressing both technical usability and patient-specific concerns.

3.2.3 Thematic Analysis

Thematic analysis is a qualitative method for identifying, analysing, and interpreting patterns or themes within data. Introduced by Braun and Clarke [167], it is a flexible and systematic approach that can be applied across a variety of theoretical and epistemological frameworks. The purpose of thematic analysis is to uncover meaningful patterns within the data, providing insights into participants' perspectives, behaviours, and experiences. This method is particularly suited to exploring complex or multifaceted issues, as it allows researchers to distil large datasets into concise, interpretable themes.

Thematic analysis is typically conducted through six iterative phases:

1. Familiarisation with the data: Immersing oneself in the dataset by reading transcripts and taking initial notes.
2. Generating initial codes: Identifying significant features of the data systematically.
3. Searching for themes: Grouping codes into broader themes that represent shared ideas.

4. Reviewing themes: Refining the themes to ensure coherence and representativeness.
5. Defining and naming themes: Articulating the central essence of each theme.
6. Producing the report: Synthesising themes into a narrative supported by evidence from the data.

3.3 Methodology

3.3.1 Research Design

This exploratory study employed a single centre, prospective, qualitative research design to gain in-depth insights into the perspectives of cancer-patients and oncologists on pain assessment and the potential use of AI in this context. Semi-structured interviews were chosen as the primary data collection method to allow for flexibility in exploring participants' experiences and opinions. Data were analysed by performing a thematic analysis (TA).

This design was selected to capture deep, rich insights into individuals' experiences and attitudes. By using this approach, the study aimed to identify key themes and patterns that could inform the development of an AI-based pain assessment model.

The Standards for Reporting Qualitative Research [168] guided the reporting of this study, to demonstrate the transparency of all aspects of the qualitative research, see Appendix B.

3.3.2 Study Participants

Two groups of participants were included in this study: 1) cancer patients, and 2) medical oncologists. Eligible patients were adults (18 years or older) with a confirmed cancer diagnosis who had experienced cancer-related pain in the past month. Medical oncologists with a minimum of 2 years of clinical experience were eligible to participate. All eligibility criteria could be found in Table 3.1.

Participants initially were recruited from the Erasmus University Medical Centre (EMC) located in Rotterdam, the Netherlands. Recruitment was conducted by a dedicated researcher (MK), who employed different strategies tailored to each group. No incentives were offered for participation.

Eligible patients were identified by reviewing admission descriptions and outpatient visit schedules recorded in the Electronic Medical Record (EMR) system of the EMC oncology department. Based on these records, the researcher approached potential participants either in the oncology ward or at the end of their outpatient visits, after consultation with the treating oncologist. Patients were informed about the study's purpose and procedures during a personal conversation with the researcher. They were provided with a participant information letter and an informed consent form. At least one day was given for patients to review the materials, ask questions, and consider their participation. If the patient decided to participate, both the patient and the researcher signed the informed consent form. Interview dates and times were subsequently scheduled according to the patient's availability.

Table 3.1 Eligibility Criteria

Cancer patients	
Inclusion	*Exclusion*
Adult (≥18 years) Confirmed cancer diagnosis Experienced cancer-related pain in the past month Receives or received treatment for cancer-related pain	Does not speak Dutch or English Unable to understand and give informed consent to participate in this study Does not use a smartphone for professional or personal purposes at least weekly or is unfamiliar with basic smartphone functionalities (e.g., using apps, sending messages, or recording audio)
Medical Oncologists	
Inclusion	*Exclusion*
Employed as a medical oncologist ≥ 2 years of clinical experience with treating cancer-related pain	Does not speak Dutch or English Does not use a smartphone for professional or personal purposes at least weekly or is unfamiliar with basic smartphone functionalities (e.g., using apps, sending messages, or recording audio)

Eligible oncologists were identified through the research team's professional network and approached via email. The email included a brief explanation of the study and an invitation to participate. Interested oncologists received a detailed information letter and an informed consent form. Upon agreement, they provided written consent, and an interview was scheduled at a mutually convenient time.

3.3.3 Ethical Considerations

Ethical approval for the study was obtained from the medical ethics review committee of the EMC, who reviewed the study protocol (MEC-2024-0743) made by MK. All participants were provided with detailed information about the study, including its objectives, procedures, and potential risks by providing a participants information letter and verbal explanation. Participants were required to give written consent before participation.

To protect participant privacy, all interviews were pseudonymized, and identifying information was removed from the transcripts. Audio recordings were stored on secure, encrypted servers, accessible only to researcher MK. Participants were informed of their right to withdraw from the study at any time without providing a reason.

3.3.4 Procedure

Semi-structured interviews with oncologists were conducted between January 2025 and February 2025 by one researcher (MK). The interviews with cancer-patients started February 2025 and are still ongoing. Participants attended the interviews individually and were conducted in a quiet,

private setting to ensure confidentiality. The interviews were conducted either in person or via a secure online video conferencing platform, depending on their preferences and availability.

The interviews were created to last between 30 and 60 minutes, depending on the length of the answers given by the participant. Before the interview started, the participants were informed about the research project, and the interviewer's (MK) professional background, role and training. With participants' consent, interviews were then conducted and audio-recorded using both a mobile phone and a computer. At the beginning of the interview, participant characteristics were collected. For oncologists, this included sex [M/F], age [years], years of experience [years], and the (estimated) frequency with which they treat patients experiencing cancer-related pain [never, rarely, sometimes, regularly, often]. For patients, demographics included sex, age, type of cancer, current pain score, highest pain score in the past three months, and whether they were receiving treatment for their pain.

The interview was divided into two parts and covered five different sections:

1. Perspectives on the current pain assessment process:
    a. Current pain assessment process
    b. Challenges related to the current pain assessments
    c. Ideas for improvement

Intermezzo - Explanation and demonstration of the AI-based pain assessment tool concept

2. Acceptance of the AI-based pain assessment tool:
    d. Attitudes towards the AI-based pain assessment tool
    e. Design and implementation preferences

After the first part of the interview, the interviewer introduced the concept of the AI-based APA tool being developed by the research group. A clickable prototype, created by Innovattic (a software company located in Delft, the Netherlands), of the concept was demonstrated, see Figure 12. The prototype showcased an application designed for patients to capture audiovisual data using the front camera. In this application, the patient is guided through a specific task while being recorded. After completing the recording, the patient can submit it through the app. The AI model integrated into the application then analyses the recording and presents its assessment within the app.

The second part of the interview protocol was informed by the constructs incorporated in the mTAM of Schnall et al. [162]. This model was selected as a theoretical framework because it offers a structured approach to understanding how users evaluate and adopt mobile health technologies. The constructs and applied definitions are outlined in Table 3.2 and the operationalisation of the constructs could be found in Appendix C. The interview protocol comprised open-ended questions and follow-up questions / prompts, which are detailed for the interviews with oncologists in Appendix D and are fully outlined in the additionally provided interview protocol documents for patients and oncologists. This format of the protocol meant to encourage in-depth discussions and personal insights, and to clarify questions if necessary.

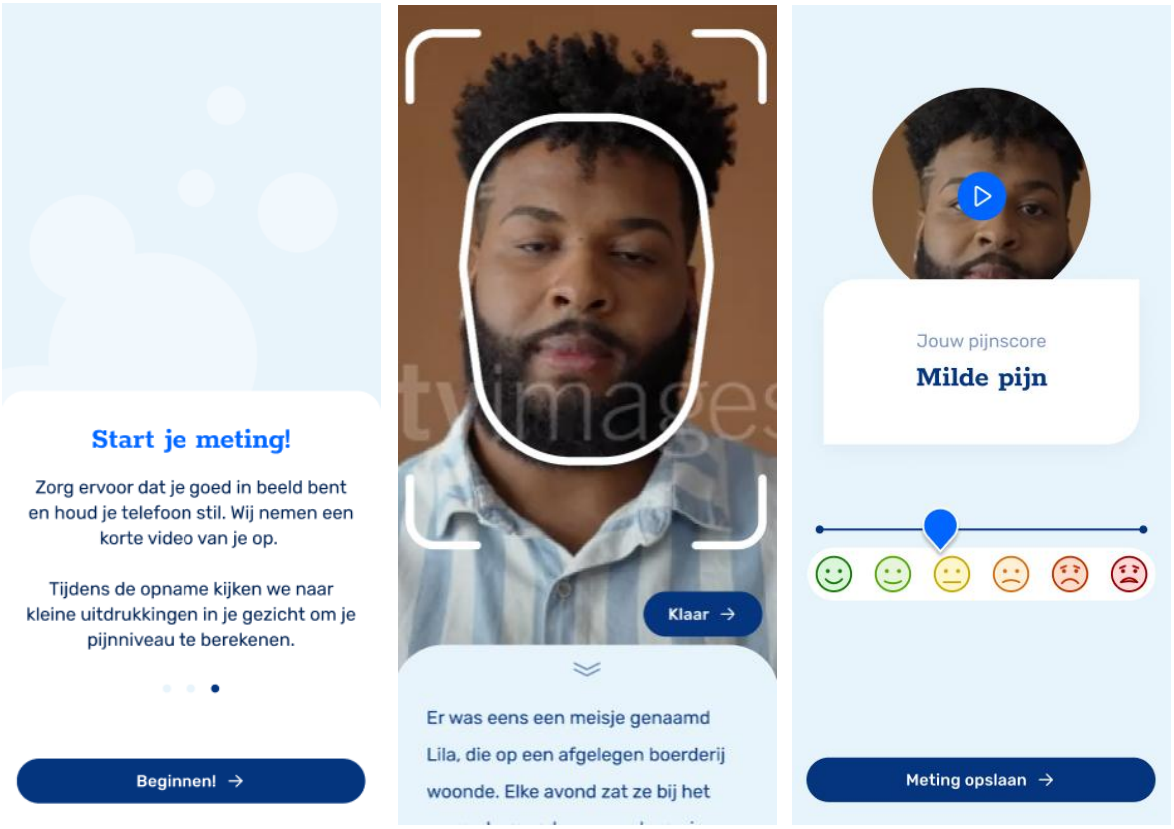

Figure 12 - Screenshots of the Dutch clickable prototype developed by Innovattic: a) Explanation of the recording task, b) Prompt recording task, and c) Presented outcome of the AI-model

Table 3.2 Constructs and applied definitions based on the mTAM

Construct	*Applied Definition*
Attitude towards Using (A)	The overall positive or negative evaluation that a participant holds regarding the use of the AI-based pain assessment tool.
Behavioural Intention to Use (BI)	The likelihood that a participant intends to use the AI-based pain assessment tool in the future.
Perceived Usefulness (PU)	The degree to which a participant believes that using an AI-based pain assessment tool will be advantageous to him/her.
Perceived Ease of Use (PEOU)	The degree to which a participant believes that using an AI-based pain assessment tool will be free of effort.
Trust (T)	The participant's belief that the system will operate responsibly, fairly, and without exploiting the vulnerabilities of patients or clinicians.
Perceived Risks (PR)	The participant's perception of uncertainty and potential negative consequences associated with using the AI-based pain assessment tool.

Before the study began, the interview protocols were piloted with one cancer patient and one individual who simulated the role of an oncologist. This helped refine the questions and words for clarity and ease of understanding (pilot data not presented here).

During the interview, the interviewer adopted a flexible approach, allowing participants to elaborate on their experiences and perspectives while ensuring that all predefined topics were addressed. After each section of questions, participants were asked if there was anything they would like to add before moving on to the next section. This approach ensured a balance between maintaining the structure of the protocol, adapting to the natural flow of the conversation, and ensuring that their perspectives were comprehensively captured.

Additional interviews were conducted until data saturation was achieved, defined as the point at which limited new insights or themes emerged from additional interviews [169].

3.3.5 Data Analysis

Each audio-recorded interview was transcribed verbatim by the interviewer (MK), adhering to the transcription protocol outlined in Appendix E. The transcripts were imported into ATLAS.ti, V25 for Windows, a software tool widely used for structuring and conducting qualitative analyses. Dutch transcripts were translated into English by MK to enable review by non-Dutch-speaking members of the research team and to ensure that a broader accessibility of the findings.

To explore how oncologists assess and manage cancer-related pain, a process mapping exercise was first conducted. MK reviewed and coded the transcripts to identify key components of the pain assessment workflow, such as the tools used and the timing and context of assessment. The codes were grouped into stages of the process and synthesised into a structured outline. To visually communicate the flow of pain assessment and its influencing factors, a process map was created to support a clearer understanding of the process and its contextual challenges.

Next, for the qualitative analysis reflexive TA was used, guided by Braun and Clarke's six-phase approach and recommendations [167]. This method was chosen for its flexibility and suitability in exploring complex, contextual experiences. It enabled both semantic (explicit) and latent (underlying) meanings to be captured, providing a comprehensive understanding of the data.

TA was performed using a hybrid inductive and deductive approach. Sections a, b, c, and e of the interviews – i.e. assessment process, challenges, ideas for improvement and design and implementation preferences – were analysed inductively to allow for an open exploration of participants' perspectives and themes to develop directly from participants' responses. Section d – i.e. attitudes towards the AI-based pian assessment tool – was analysed using a directed, deductive approach informed by the mobile health Technology Acceptance Model (mTAM) [144]. Parent codes were defined based on the mTAM constructs, while subthemes were identified inductively. The inductive component allowed for an open exploration of participants' perspectives, while the deductive component provided structure, ensuring alignment with established theoretical frameworks. Responses that fell outside the initial framework were reviewed and, if needed, used to refine the model or captured as new insights.

The coding and theme development were conducted iteratively by MK, with feedback and review from HT and MM. Initial codes were grouped into conceptual clusters, and thematic maps were created to visualise relationships. Meanings united by a central organising concept were used as the foundation for the initial theme identification. Final themes were reviewed collaboratively and organised into a coherent structure. Representative quotes were selected to support the presentation of results.

3.4 Results

3.4.1 Description of Participants

Data saturation was reached for the group of oncologists. In total, 11 medical oncologists participated in this interview study, see Table 3.3. The interviews lasted 40-60 minutes. At the moment, two patients participated in this study. Data saturation is not yet achieved for this patient group, due to the limited time of this thesis. Interviews with patients will continue beyond the scope of this report and findings from these two patient interviews are not included in this report.

3.4.2 Pain Assessment Process & Context Mapping

The pain assessment process for an oncologist focuses on gathering information about the patient's pain state to guide pain management decisions and ultimately improve the patient's pain experience. To obtain this information, oncologists interact with patients, other healthcare providers, important others for the patient and digital systems. Given the central role of information gathering in pain assessment, the oncology department (and hospital in general) offer various ways for patients to report their pain. During interviews with oncologists, several interactions were identified through which patients can communicate their pain experiences. Important interactions that were identified for the oncologist and patient were mapped in Figure 13. See Appendix F for more information on the interactions mapping.

As can be extracted from those interactions, the pain assessment process occurs within a specific clinical context and even differs depending on the setting and mode of interaction between the oncologist and the patient. Based on interviews with oncologists, four key contexts were identified:

1. Inpatient consultation: Assessing pain during a face-to-face consultation with a hospitalised patient
2. Outpatient consultation (in-person): Evaluating pain during a scheduled in-person visit with a patient in an outpatient setting
3. Outpatient consultation (remote): Conducting a pain assessment via telephone or video consultations
4. Indirect pain assessment: Evaluating a patient's pain without direct interaction, relying on medical records, reports from healthcare specialists, such as colleague oncologists or nurses, or input from important others.

Table 3.3 Participant characteristics of medical oncologists

Participant	*Sex (M/F)*	*Age (y)*	*Exp. (y)*	*Specialty*	*Freq. (ord.)*
O01	M	37	4	Urologic oncology	Regularly
O02	F	39	10	Urologic oncology Phase-1 trials	Regularly
O03	F	56	20	Breast cancer oncology	Regularly
O04	M	41	8	Clinical oncology Melanoma and renal oncology Immunotherapy	Regularly
O05	F	48	13	Pancreatic and biliary tract oncology	Regularly
O06	F	45	10	Melanoma and renal oncology Immunotherapy	Sometimes
O07	M	35	6	No specialty	Often
O08	M	62	28	Gastrointestinal oncology Neuroendocrine oncology Phase-1 trials	Regularly
O09	F	48	18	Palliative oncology Sarcoma	Often
O10	M	37	4	Phase-1 trials	Regularly-Often
O11	F	53	21	Head and neck oncology Gastrointestinal oncology	Regularly
n = 11	5 M; 6 F	46 ± 9	13 ± 8		

Abbreviations: F: female, M: male, y: years, Exp.: years of experience as a medical oncologist including residency, Specialty: specialty within the field of oncology, Freq.: frequency of contact with patients for cancer-related pain ("never" – "rarely" – "sometimes" – "regularly" – "often"), ord.: ordinal scale

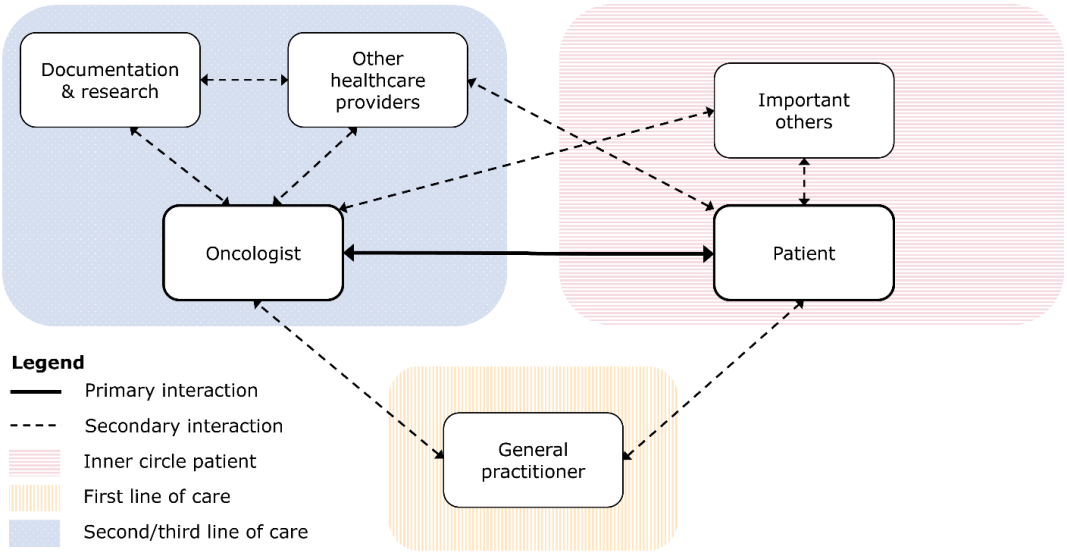

Figure 13 - Mapping of the interactions patients and oncologists have regarding pain assessment, derived from the interviews with oncologists. The most important interaction is the interaction between the oncologist and the patient. All other interactions are secondary (dotted lines). The patient is closely related to the people within the patients' inner circle (pink circle). The patient has the option to interact with the first line of care (yellow circle), being the general practitioner, and the second/third line of care (blue circle), being healthcare providers in the hospital. The oncologist could interact with the same persons but could in addition to this also interact with the digital systems for documentation and research.

Figure 14 - Process mapping of the pain assessment and management as performed by the oncologist. Seven steps were identified: 1) Identifying the need to discuss pain, 2) Initiating the pain conversation, 3) Conducting the pain anamnesis, 4) Decision-making on the pain management, 5) Communicating pain management decisions, 6) Documenting the assessment and decisions, and 7) Follow-up and monitoring. Steps 2, 3, and 5 ideally involve direct interaction with the patient and are therefore placed between the patient and the oncologist. Steps 1, 4, and 7 primarily consist of oncologists' considerations and clinical reasoning to reach a conclusion before proceeding to the next step. Step 6 involves interactions with digital systems for documentation and record-keeping.

The preferred approach was direct interaction, as the patient is the one experiencing pain and can provide the most valuable information needed for an accurate pain assessment. Indirect interaction was only mentioned as an alternative when direct contact was not possible or as a supplement to direct assessment.

Although the pain assessment and management process varied depending on the context, several key stages that oncologists consistently followed could be identified from the interviews, see Figure 14.The seven key stages are:

1) Identifying the need to discuss pain
   All but one oncologist (O11) highlighted that pain isn't discussed with all patients, although it is in the protocol for outpatient consultations. The reasons for this are that it is not always perceived as necessary to discuss it and that they have to prioritise topics during their consultations. One oncologist explained in response to the question 'How often do you discuss pain with your patients?':

   "Almost always. Well, when I know that pain is an issue, I check in every consultation to see if the current pain management is sufficient. And always during the first intake. But if there are no pain complaints at all, then sometimes it fades into the background — but almost always." – O07

   Therefore, the first step in assessing pain is determining whether it needs to be addressed with the patient (or, if needed, another person). This decision is typically based on :1) the degree to which pain is expected to be experienced by the patient, 2) the degree to which the patient is expected to mention pain as a problem if experienced and 3) the degree to which the oncologist sees himself as responsible for discussing and/or treating pain.
2) Initiating the pain conversation
   Once the need to discuss pain is identified, the oncologist or patient initiates the conversation on pain experience. This stage often involves establishing rapport and ensuring that the patient feels comfortable discussing their pain experience. It also includes the oncologist observing the direction the conversation takes and noting whether the patient independently introduces the topic of pain. Both can offer valuable insights into the patient's desire to talk about it and the perceived burden of pain on their daily life that could be expected by the oncologist.
3) Conducting the pain anamnesis
   During this stage, the oncologists conduct a thorough pain anamnesis, where they ask the patient about several aspects of pain, including the intensity, duration, and characteristics of their pain. This is a critical stage for gathering information.
4) Decision-making on the pain management actions
   After collecting the information from the patient (or best other available person), oncologists evaluate all available data, including patient-reported pain levels, type of pain, perceived origin of pain, medical history, the oncologists' medical knowledge, treatment-options and any other relevant factors. If important information is missing and the patient

can't provide it, the oncologist could interact with other people or systems, as mapped in Figure 14, to retrieve it. After considering all factors, oncologists decide on the appropriate course of action for pain management.

5) Communicating the pain management decisions to the patient
   Following the evaluation, oncologists communicate the pain management plan to the patient. Some (O04, O08) emphasised the importance of explaining the rationale behind the chosen approach, as clear communication fosters understanding and shared decision-making. One oncologist explained:

   "Most people are very reasonable, very fair, and good. It is easy to explain to them why you make certain choices the way you do. (...) Essentially, I have the impression that you can create a good plan together, especially when you clearly state, 'I will do this, but not that. This is why, that is why.' You know, that's really the explanation behind the policy."
   – O04

6) Documenting the assessment and treatment decisions
   All aspects of the pain assessment and the subsequent decisions are documented for future reference, ensuring continuity of care and compliance with medical protocols.
7) Follow-up and monitoring pain management
   The final stage involves scheduling follow-up appointments to monitor the effectiveness of the pain management strategies and perform a new pain assessment if needed.

While the process varies depending on the oncologists' preferences and routines, as well as logistical factors and the patient's individual circumstances, these key stages form the backbone of the current pain assessment approach found in oncological practice of the interviewed medical oncologists' Medical Centre. A more detailed description of the stages and the topic summaries of the oncologists' considerations at those stages are provided in Appendix F.

3.4.3 Current Pain Assessment Challenges

The analysis of participants' responses identified five key themes, providing a comprehensive framework for understanding the challenges oncologists face in the current pain assessment and management process, see ... . For clarity, numerical identifiers have been assigned to the themes. However, in practice, the themes are interconnected and ranked based on the line of the story that is told. The first theme focuses on pain as a complex, dynamic and subjective experience of an individual that integrates physical, emotional and social dimensions. Oncologists reported that this multidimensional and subjective nature of pain makes assessment inherently challenging. The second theme concerns an ethical issue, that oncologists perceived as a challenge, but that also could reflect broader societal debates about the division of responsibility in healthcare – specifically, the extent to which pain management is the patient's responsibility versus the oncologist's duty to intervene. The responsibility for assessing and managing pain is shared between patient and oncologist, but raises ethical questions about ownership, self-management, and medical intervention. The third focuses on the challenge of expressing and interpreting pain. Effective pain assessment depends on overcoming communication barriers, where both patients and oncologists must navigate verbal, non-verbal, and interpretative challenges. As a fourth

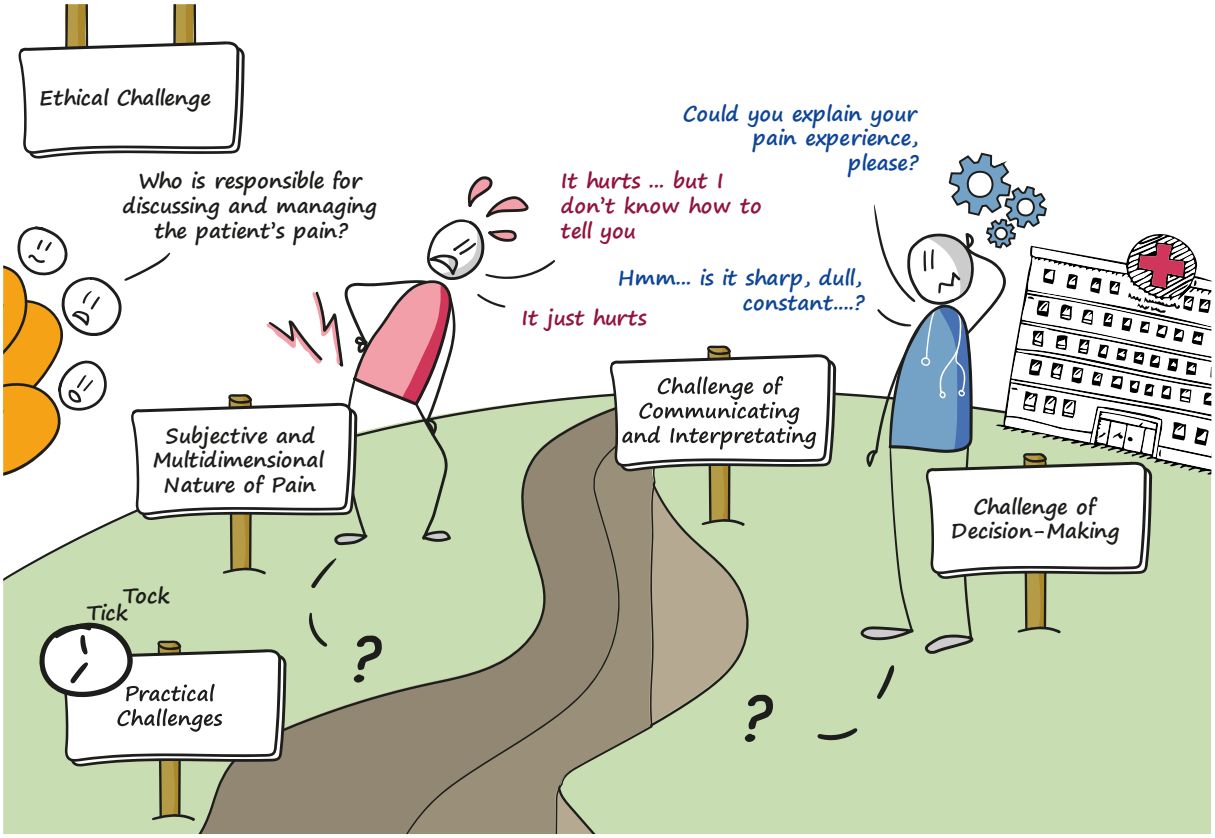

Figure 15 - Illustrated summary of the five key challenges in cancer pain assessment identified through thematic analysis. In an attempt to assess and manage pain, the oncologist initiates a conversation based on visible non-verbal cues of discomfort. The patient, however, struggles to verbalise their pain experience, complicating mutual understanding (Challenge of Communicating and Interpreting). This difficulty is compounded by the Subjective and Multidimensional Nature of Pain, as pain integrates physical, emotional, and social components that cannot be objectively measured. While navigating vague or inconsistent information, the oncologist must weigh multiple factors to make a well-informed treatment decision, balancing clinical observations, patient preferences, and feasibility (Challenge of Decision-Making). These tasks become even more difficult in real-world practice due to Practical Challenges, such as time constraints, limited continuity of care, and distance in outpatient settings. Finally, the Ethical Challenge reflects a broader tension around responsibility: who is ultimately accountable for addressing the patient's pain – the patient, the oncologist, or the healthcare system as a whole?

theme, the challenge of decision-making is considered. Oncologists must balance subjective patient reports, clinical reasoning, practical possibilities and their own capabilities to make informed treatment decisions in a sometimes-uncertain landscape. Combining all this information and making decisions forms the task of the oncologist but is also considered a challenge itself. Lastly, the context in which pain assessment takes place forms the fifth theme. The context shapes the ability to monitor, follow-up and act on pain-related concerns, leading to practical challenges.

3.4.3.1 Theme 1 – The Subjective and Multidimensional Challenge

Oncologists navigate a fundamental tension in pain assessment: pain is a deeply subjective and multidimensional experience, yet they, as an outsider to this experience, must capture this and all its dimensions. Unlike other clinical parameters, pain lacks an objective reference point - its presence, intensity, and impact manifests mainly within the realm of the patient's own perception. As one oncologist put it:

"I always call it pain experience because that is what pain is, of course. It really is an experience." - O11

This framing emphasizes that pain is not just a physical sensation but a deeply personal experience, shaped by emotions, beliefs, and circumstances. While medical frameworks often define pain as a physiological response, oncologists recognize that it cannot be separated from the person experiencing it. One oncologist reflected on the shift in perspective required to acknowledge this complexity:

"The difficult thing about pain is, of course, that it is always subjective. [...] I was taught in medical school, 'Pain is what the patient says it is.' At first, I found that very difficult because I am a scientist, and I want to objectify things. But ultimately, at the end of the day, that is the reality." - O07

This definition of pain, echoed by many oncologists, underscores that pain is not a uniform sensation but an individual experience shaped by numerous factors. Each patient perceives pain differently, influenced by character, emotional state, personality, culture, and beliefs about pain and illness as reported by the oncologists.

"Of course, we also have patients who are very afraid, extremely afraid, who raise the alarm at every little pain, especially because they are terrified that it means something is wrong with their cancer." - O09

This interplay between physical and emotional factors means that patients with similar clinical presentations may report vastly different levels of pain. Some patients normalize pain as part of their condition, while others perceive even mild pain as overwhelming:

"There is, of course, a great deal of variation in that [the expression of pain]. Some patients think pain is just part of their condition and don't even mention it. And then there are patients who experience even very mild pain as extremely burdensome, dominating the entire conversation – and, of course, everything in between." - O04

But also cultural background and societal norms shape how patients perceive and relate to pain:

"You just know that people from different cultural backgrounds have very different views. For example, some believe that morphine is bad, just to name one. But there are also cultures where it is very common that if you are sick, you stay in bed and act very ill. So, they often have a high level of illness perception and also a kind of illness benefit, because it is expected in their culture that they will be cared for by their family. And so, all symptoms are heavily emphasized." - O04

These individual, emotional, and cultural differences in pain experience and expression reinforce the idea that pain cannot be treated purely as a somatic phenomenon. The multidimensional nature of pain extends beyond personal beliefs to include the interplay between physical symptoms, emotional distress, and cognitive interpretations:

"Pain is not just one thing. I think pain is really a complex of different elements, including, for example, fear and worry, which can play a role in the pain experience. That makes it difficult to properly assess the severity of the pain." - O02

Oncologists recognize that pain must be assessed in relation to the whole patient – their story, their affective states, and their broader life circumstances. Focusing solely on one dimension of pain – such as somatic symptoms – risks overlooking the broader distress a patient may feel:

"There are so many different facets to pain experience and pain, things that come with pain. I think that is different for everyone, and I notice that if I approach it one way, it doesn't always address all questions or all the dissatisfaction a patient may have." - O10

Thus, pain remains a fundamentally multidimensional phenomenon, requiring oncologists to continuously interpret, contextualize, and adapt their assessment strategies. The challenge of pain assessment is not merely about measuring intensity but about understanding the patient's lived experience – one that is shaped by a complex interplay of biological, emotional, and social factors.

3.4.3.2 Theme 2 – The Ethical Challenge

Pain assessment in oncology is not just a clinical task but also an ethical challenge. Oncologists must determine who holds responsibility for managing pain – the patient, who experiences it, the oncologist, who has the means to treat it, or the multidisciplinary team of healthcare professionals, who altogether treat the patient. The tension between patient autonomy and medical intervention presents a recurring dilemma in oncological care.

A central view among oncologists is that the patient is the owner of their disease and, by extension, their pain:

"Very simply put, perhaps the biggest challenge is: Who owns the problem? Is it the patient, or is it the doctor? In principle, it's the patient." - O08

This perspective aligns with the broader principle of patient autonomy and self-management, which assumes that individuals are also responsible for their care. Oncologists therefore encourage patient to be proactive and try to lower the barrier to report pain if present. This is why oncologists expect patients to recognise and report their own pain.

"I try as much as possible to make sure people have the space to say, 'That's all well and good, but can I talk to you about my pain?' So I do think a part of the responsibility also lies with the person experiencing the pain." - O08

"And when you ask, 'How are you?' and 'Do you have any complaints?', you hope they will say something." - O04

"On the moments that they are with me, they say they're doing fine. Then I feel I should assume that they are actually doing fine." - O10

Despite efforts to encourage openness, oncologists frequently encounter patients who are reluctant to report pain. They speculate that this reluctance stems from multiple factors, including personality traits, emotional and cognitive aspects of pain, and perceived barriers to contacting

their oncologist. This raises an ethical question: to what extent should oncologists proactively assess pain rather than relying on patients to report it? Some oncologists worry that being too proactive in assessing pain might override patient autonomy, while others see an ethical obligation to ensure that pain does not go untreated. The latter group decided to consistently discuss pain during each moment of contact.

Another thing that might affect how responsible the oncologist feels to discuss and mange pain, is the perception of pain management as either an individual or a shared responsibility. While this was never explicitly stated about themselves, one oncologist mentioned that some colleagues feel less compelled to take an active role in pain management:

"Not everyone feels called to treat pain. [...] Some colleagues say, 'I'm an oncologist, I treat cancer—I'm not here to manage pain every day. That's someone else's job.'" – O09

This statement suggests that some oncologists see pain management as a multidisciplinary responsibility, which may reduce their emphasis on pain assessment as an individual task.

Together with the degree to which pain is expected and is expected to be reported by the patient, this sense of responsibility shapes the oncologists perceived need to discuss pain with the patient, see Appendix F.

The variation in oncologists' attitudes towards pain assessment highlights a key ethical challenge – how actively should they screen for pain? Some take a patient-led approach, assuming that if a patient does not bring up pain, it is not a major issue. Others make deliberate efforts to initiate discussions, ensuring that pain is not overlooked. The dilemma lies in striking a balance: relying entirely on patient-initiated discussions may leave some patients suffering in silence, while taking a more forceful approach could feel intrusive or unnecessary. The question of who "owns" the pain problem remains unresolved, reflecting the broader complexity of pain management in oncology.

3.4.3.3 Theme 3 - The Challenge of Communication and Interpretation

Pain assessment in oncology is fundamentally dependent on communication, yet it remains one of the most challenging aspects of the process. Patients must verbalize their pain experience, while oncologists must interpret and validate these subjective reports. However, oncologists report that both expression and interpretation are prone to barriers. This results in a complex interplay between verbal and non-verbal communication, questioning strategies, and observational assessments.

Patients often struggle to articulate their pain experience in a way that is clinically useful. Pain, by nature, is difficult to articulate. Oncologist noted that many patients provide vague or non-specific responses:

"When I ask, 'Can you describe your pain?', patients often just say, 'It's pain.' Then I have to use more closed-ended questions to guide them." - O02

"When you ask, 'How was your pain in the past three weeks?', you often get generalized answers." - O07

This communication barrier means oncologists must rely on structured questioning techniques to break pain down into more concrete components – such as location, duration, intensity, and impact on daily life. However, even with careful questioning, the descriptions remain subjective and open to interpretation.

Beyond the general difficulty of describing pain, oncologist identified that specific barriers further complicate expression:

1) Language barriers: Patients who do not speak the same language as their oncologist, pain descriptions may become oversimplified or misunderstood:

"The main challenge remains the language barrier. 'Doctor, pain, pain, pain,' [spoken with an accent] 'Where do you have pain?' 'Here.' [Points to a spot on their body.] That makes it really difficult." - O08

2) Limited cognitive abilities: Some patients struggle to articulate their pain or understand instructions due to limited cognitive abilities:

"With people with limited understanding, it's really hard to explain how they should use pain medication at home. And also in how they express their pain." - O03

3) Self-informed patients: Some patients enter consultations with medical terminology they have read online, sometimes misrepresenting their pain by using diagnostic language rather than describing their symptoms:

"Patients don't say, 'I have pain in my left flank' anymore; they say, 'I have pain in my spleen.' Or they say, 'I have kidney pain.' That makes taking a proper history more difficult." - O03

These barriers illustrate a core limitation of self-reporting: pain exists within the patient's experience, but their ability to communicate it effectively varies significantly.

Beyond difficulties in articulation, oncologists identified substantial variability in how patients express and articulate pain. Some patients are highly vocal about their pain, while others are hesitant to report it at all:

"How people express their pain experience – how they are used to presenting themselves to those around them – greatly influences how their pain is discussed in the consultation room." - O10

Since verbal reports are not always sufficient, oncologists often rely on indirect clues to assess and interpret pain. These clues include observations of non-verbal behaviour, physical functioning, and the patient's use of pain medication:

"You also look at whether people seem to be in pain – that's more common in the clinical setting, but even in outpatient care, you see it when patients enter the room and get up from their chair." - O06

"Of course, you always look at what kind of pain medication they're already taking. And from that, you can often infer something – I mean, if people are taking a lot of rescue medication in a day, then you estimate that their pain is probably high, or at least not well controlled." – O05

While these indirect cues can be helpful, oncologists also emphasised their limitations. Pain is a dynamic and fluctuating experience, and any observation made during a consultation offers only a snapshot of the patient's condition. As one oncologist noted:

"You always take non-verbal communication into account, but you have to realize that it's just a snapshot. Someone might be fine now but in severe pain at night." - O05

Even with careful questioning and observation, misunderstandings remain inevitable. One oncologist reflected on this persistent challenge:

"There will always be a gap between what a patient experiences, what they communicate to me, and what I interpret from that. It will never be 100% perfect." - O08

To bridge this gap, oncologists emphasize repeated questioning, verification strategies, and experience-based intuition. However, they acknowledge that no method can completely eliminate uncertainty. The balance between patient self-report and oncologist interpretation remains an ongoing challenge in clinical practice, and a pain assessment still is an ongoing interpretative process.

3.4.3.4 Theme 4 – The Challenge of Decision-Making

Oncologists face another fundamental challenge in pain management: deciding how to act on complex, often conflicting, and inherently subjective pain reports. This decision-making process requires balancing the goal of pain relief with treatment feasibility, patient preferences, and potential risks, all while working in an environment of uncertainty.

A recurring theme in the interviews was that oncologists do not necessarily aim for complete pain elimination but rather for acceptable or tolerable pain levels that allow for a manageable quality of life. This shift is influenced by two factors: 1) focus on the patients' desire for changes in pain management, and 2) the practical limitations of pain treatment, where pain relief often comes at the cost of side effects, dependency risks, and diminishing returns in pain reduction.

Oncologists described how the impact of pain on the life of the patient is overlooked and how they must assess not just pain intensity but also its impact on daily life and the patient's perception of tolerability:

"[There are patients who say] 'I don't want any pain. I can't handle it. It must be an NRS [Numerical Rating Scale] 0.' And then there are also patients who say, 'I have an NRS of 7, fine. I can deal with it.' There are huge differences in that regard." – O09

"We talk a lot about the pain score in the clinic, but we don't actually ask whether that number reflects something tolerable. And that's a huge variation – some people find a 7 unbearable, others find a 7 quite mild. [...] So we might consider a score of 7 to be very high, but we forget to ask, 'Is 7 something you can manage?' And that's where the real meaning lies." – O04

By shifting their focus from absolute pain reduction to pain acceptability, oncologists acknowledge that pain is a lived experience rather than a purely medical symptom. This requires a patient-centred approach, where treatment decisions depend not just on clinical data but on the patient's individual experience, values, and coping strategies.

However, translating this approach into practice is not always straightforward. One of the greatest challenges in decision-making is handling discrepancies between different sources of information. Oncologists frequently encounter cases where self-reported pain intensity does not align with their clinical observations, or information received from others:

"And that's not always the case, right? Last week, I saw someone where I thought, 'Yes, I've seen your scan. I've seen your lab results. You must be in excruciating pain.' But they absolutely refused to take morphine. That is really difficult to assess, I think. So, that's what I find the biggest challenge." – O01

"Some people say, 'My pain is unbearable,' yet they sit at the table doing puzzles, eating and drinking, and then get up and walk to the bathroom without issues. But they insist, 'I have terrible pain.' That's a difficult situation."- O04

To resolve these discrepancies, oncologists try to deepen, objectify, standardise and validate the story of the patient. Examples of efforts to validate the reports are additional questioning, follow-up, and taking the use of medication and observations into account, as mentioned in theme 3 (section 3.4.3.3). However, trying to validate and objectify pain, creates a tension:

"Clinically, we can monitor patients closely, which allows us to add some objectivity to subjectivity. But even that is risky. We have more information about how pain affects behaviour, but it's still difficult." – O10

When trying to standardize pain assessments, pain scores could be used. Oncologists report to use pain scores, specifically the NRS-score. They do so, because it is part of standard protocol, or because they believe it provides insights into pain trends within a patient:

"One patient's 8 is another's 3. You have to know the patient – some lie still with a 10, others are walking around with a 6. That's why I place scores in context." – O01

"We hope that a patient at least uses the same standard for themselves – so if today is a 7 and tomorrow an 8, we know it's worsening." – O04

Oncologists described pain scores as too simplistic to capture the complexity of pain, leading to concerns that they: 1) lack direct correlation to pain tolerability, 2) vary significantly between patients, and 3) oversimply the multidimensional nature of pain. This suggests that while pain scores remain a necessary tool, they are insufficient for decision-making unless combined with patient history, functional assessments, and clinical judgment.

Besides those attempts, as mentioned, oncologists also rely on their relationship with the patient, their clinical experience and intuition to navigate discrepancies in pain reports. Familiarity with a patient allows them to distinguish between what is typical for that individual and what signals a significant change. However, when treating an unfamiliar patient, this becomes more difficult, underscoring the importance of continuity for oncologists:

"You have to know your patient, understand what their baseline pain score is, and whether it is above or below that – I find that very difficult." - O01

Experienced oncologists often rely on their intuition, do follow-up questions, and make sure they get the whole story:

"If someone says, 'I have a pain score of 8,' I always follow up – always. I think that doesn't always happen. If my colleagues are on duty over the weekend and the nurses report a pain score of 8, the immediate reaction is, 'Increase the dose.' But I don't do that. I go see the patient first to determine if that 8 is actually a realistic 8." – O09

While clinical intuition plays a crucial role, all oncologists recognise that no matter the contradicting information, the story of the patient is the most important component in pain assessment and management. Otherwise, there is a risk of allowing subjective impressions to overshadow patient-reported pain:

"There are moments of doubt – does the patient really have that much pain? And then you realize, you can't override their experience just because it doesn't align with what you expect." – O08

This reflects a fundamental challenge: oncologists must decide how much weight to give to patient narratives versus their own clinical reasoning.

Beyond assessment, oncologists also face challenges in the feasibility of pain treatment. Even when a patient expresses significant pain, treatment decisions are constrained by determining the cause of pain, balancing pain relief with side effects and determining use of and adherence to pain medication.

"A major challenge is always finding the right balance between the side effects of pain medication and its effect on pain. Sometimes you want to give more, but you reach the limits of what the body can tolerate." – O07

These challenges highlight that pain management is not a linear process but a complex, ongoing balancing act between patient needs, clinical reasoning, and the constraints of medical treatment options.

3.4.3.5 Theme 5 – The Practical Challenges

Pain assessment in oncology is shaped by systemic constraints, including time pressures, discontinuity in care, and differences between inpatient and outpatient settings. These factors affect oncologists' ability to monitor, evaluate, and act on pain reports.

A frequently mentioned challenge was limited time, particularly in the outpatient setting, where consultations must cover multiple medical concerns within a short timeframe. Oncologists must prioritise discussions, often focusing on cancer progression and treatment options rather than symptom management. As a result, pain—and especially pain scores—may not always be addressed in depth:

"If you have a follow-up plan, you need time to explain it and provide information about the next treatments, and you only have 20 minutes. So those are definitely the challenges." – O04

"Well, time is always a factor, of course. That is [...] an important factor, which might sometimes even lead to a deliberate decision to temporarily set something aside during the initial assessment. But of course, the people who come in never deserve that." – O08

Patients themselves also contribute to this dynamic, as their primary concerns during consultations are often treatment outcomes rather than pain control:

"In the outpatient setting, time is a problem. And pain, you know, is rarely the main reason for a consultation. If a patient comes in, they don't want to start by talking about pain. They want to hear the results of their scan, which they've been anxiously waiting for all week." – O04

This limited time means oncologists must actively create space for pain discussions, which is challenging in a busy schedule:

"Do I create enough space for my patients to bring up concerns? That's a challenge—especially when I'm running behind on my clinic. Everything becomes a little shorter, a little more abrupt." – O08

Pain assessment is further complicated by disruptions in continuity. Although this is mentioned by just one oncologist (O06), it is believed that this fits in the current societal state of limited healthcare capacity. The lack of continuity in care is particularly a challenge different oncologists see the same patient at different appointments. This fragmentation can lead to inconsistencies in tracking pain over time:

"If a different oncologist sees the patient at the next appointment, they might not be aware of the previous pain discussion. That makes follow-up decisions harder." – O06

Similarly, in inpatient settings, oncologists rely on nurses' reports:

"One nurse says one thing, another says something else, and then you think, 'Wait, but yesterday they said something different.' So, you sometimes lose track of what's actually going on." – O06

Comparable challenges arise in indirect pain assessments from family members or general practitioners.

Lastly, context-based challenges are those related to the outpatient setting. Compared to inpatient settings, where pain can be monitored frequently relatively easily, outpatient pain assessment is constrained by the distance between the oncologist and the patient. Without direct observation, oncologists must rely almost entirely on self-reported pain, which presents several difficulties:

"You depend on what the patient shares with you at that moment, right? So, in the outpatient clinic, you don't have the opportunity to observe patients for a longer period, let alone in their own environment. And that's actually what you would want if you really want to get a complete picture." - O09

"Because of the distance between the doctor at the hospital and the patient at home, you don't get the full picture of how they're doing, what their pain experience is like, or how well they tolerate their pain medication." – O02

This lack of direct monitoring can lead to delays in pain reporting, as patients may not reach out when their pain worsens. Oncologists suspect that some pain cases go unnoticed. Where one oncologists thinks this is a small group, another acknowledged that the actual extent remained uncertain to her:

"That is certainly overlooked or postponed. It's not the case for the majority of patients, though. It's a minority of patients, but it definitely happens." - O02

"So actually, for the patients I have identified with pain, things seem to be going quite okay. But I don't know what we're missing – that's more where the issue lies." - O09

The combination of time constraints, discontinuity in care, and challenges related to in- and outpatient settings makes pain assessment a practical challenge in daily oncological care. While oncologists aim to remain attentive to pain, the structural limitations of clinical practice create inevitable gaps, for now.

3.4.4 Reported areas for improvement

Based on the responses to the questions of part 3 of the interview protocol, six themes related to areas for improvement were identified: 1) Improved monitoring in outpatient settings, 2) More objective pain assessment methods, 3) Capture more aspects of pain in the outpatient setting, 4) Enhancing communication and information flow, 5) Stronger collaboration between specialties, and 6) Education on a proactive approach of the patient regarding pain management. Since those reported areas for improvement are mainly in line of the expectations based on the reported challenges, these themes are further described in Appendix G.

3.4.5 Attitudes Towards AI-Based Pain Assessment Tool

The second part of the interviews focussed on the perspectives of the oncologists on the AI-based pain assessment tool. The participants' feedback centred on the five main themes of the mTAM model: perceived usefulness, perceived ease of use, perceived risks, trust, behavioural intention.

3.4.5.1 Perceived Usefulness

The usefulness theme is related to the extent to which oncologists believed that the technology would be advantageous to him or her. Participants were asked whether they perceived the tool as useful, whether they believed that it would serve a purpose to them and how it would be useful to them if so. A total of seven oncologists considered the tool useful on the condition that the tool was scientifically proven to be accurate, while three (O01, O09, and O10) expressed their reservations, and one (O07) anticipated limited usefulness.

Five subthemes were identified including: 1) improved pain detection and monitoring in the outpatient setting, 2) improved pain communication, 3) enhanced pain assessment consistency, 4) enhanced patient-engagement, and 5) conditions and barriers to usefulness. Table 3.4 presents quotes relating to the sub-themes for participants' perceptions of usefulness of the technology.

To start, oncologists perceived the concept particularly useful for providing more frequent and structured pain measurements. This way the tool allows for the creation of a clearer trend over

time, which was considered valuable for assessing a patient's pain trajectory. Rather than relying on a single point-in-time report during a consultation, they believed that tracking fluctuations and long-term patterns could provide a more comprehensive understanding of the patient's pain state, helping them make more informed treatment decisions. Being informed about the patient's pain status at any given time, along with access to a trend that visualises changes over days or weeks, could help oncologists identify patients who might not proactively report increasing pain. This, in turn, allows for timely intervention and potentially even the prevention of more severe pain episodes. Additionally, some oncologists suggested that an automated alert system based on the recorded pain trends could help prioritise patients needing urgent attention.

Following this, oncologists perceived the AI-based tool as a potential facilitator of more effective communication about pain. By providing structured and visualised pain data over time, the tool could serve as an objective reference during consultations, enabling clinicians to better assess a patient's pain trajectory. Instead of relying solely on patient recall, oncologists would have access to a more complete picture of pain trends, making discussions more data-driven and reducing uncertainty in pain reporting. Additionally, the tool could prompt oncologists to address pain issues more frequently, ensuring that pain management remains an integral part of clinical conversations.

Another potential advantage identified by oncologists was the tool's capacity to support more consistent and objective pain assessment across time and across professionals. Pain was described as a highly subjective phenomenon, making it difficult to assess reliably – particularly when different clinicians are involved in a patient's care. Several oncologists noted that current pain assessments often vary depending on who performs them, when they are performed, and how patients express their pain. In this context, the AI-based tool was viewed as a promising means to reduce this variability by providing a more standardised and reproducible input into clinical decision-making. By analysing facial expressions and vocal cues in a consistent way, the tool could help ensure greater continuity in pain evaluation, particularly in settings with rotating staff or limited time. Some oncologists also saw value in using the tool to monitor intra-patient changes over time, offering a more calibrated perspective on pain progression or treatment response.

Lastly, the tool was also seen as a way to empower patients to take a more active role in managing and understanding their pain. By regularly tracking their pain patterns, patients might not only become more aware of fluctuations and potential triggers but also gain deeper insight into their own pain experiences. Some oncologists suggested that this increased awareness could help patients recognise trends in their pain, understand what influences it, and identify whether treatments are effective over time. This process of self-monitoring could also lead to more proactive pain management, with patients recognising changes in their pain earlier and reporting them more accurately. Additionally, oncologists noted that by encouraging patients to reflect on their pain, the tool could lower the threshold for discussing pain openly, ensuring that discomfort is addressed sooner rather than being overlooked in routine consultations.

While many oncologists acknowledged the potential benefits of the AI-based pain assessment tool, several emphasized specific conditions that must be met before it could be considered truly useful. Scientific validation emerged as the most frequently emphasised condition for considering using

the tool. All but one oncologist (O07) stated that robust scientific research is essential to establish the tool's accuracy, reliability, and clinical relevance and that seeing strong evidence from these studies is a prerequisite for them to consider the tool useful in clinical practice and to trust its assessments. This scepticism aligns with the critical and evidence-based approach that defines clinical decision-making, where new tools and interventions must be rigorously tested before they are integrated into routine care. Oncologists emphasized that, without such validation, they would remain cautious about relying on AI-generated pain scores for treatment decisions, limiting the tools usefulness.

Additionally, some oncologists questioned whether the tool would provide sufficient information to meaningfully support clinical decision-making and have a real added value. They argued that pain assessment involves more than just numerical values or AI-generated predictions, as treatment decisions are based on a comprehensive understanding of the patient's overall condition, medical history, and response to previous treatments. Some oncologists felt that the AI-generated pain assessment alone would not provide enough information to justify treatment changes and that confirmation with the patient's narrative would always be necessary. When asked whether they would use the tool as a supplementary aid or a replacement for existing pain assessment methods, all oncologists stated that they would use it as an additional tool rather than a substitute. They emphasized that AI-assisted pain assessment should serve as a complementary data point, supporting clinical judgment rather than replacing direct communication with the patient. However, one oncologist (O04) suggested that, if validated as equally or more reliable, the tool could potentially replace self-reported pain scores in the future. The perception that the tool might have limited added value was more prominent when oncologists considered its use in the inpatient setting. Oncologists noted that nurses already monitor pain closely and provide real-time assessments. They questioned whether the AI-based tool would offer significant advantages over existing clinical evaluations, particularly when trained healthcare professionals already assess pain in face-to-face interactions.

Another barrier oncologists highlighted was the tool's applicability across different patient groups and clinical scenarios. They noted that certain situations may not benefit from AI-based pain assessment, particularly when direct communication with the patient is already effective or when patients themselves do not perceive added value in using the tool. Additionally, oncologists pointed out that the tool's reliance on facial expressions and vocal cues may limit its accuracy in specific patient populations, such as individuals with facial deformations, voice alterations due to illness or treatment, or neurological conditions that affect their ability to express pain verbally or nonverbally. These concerns raise questions about how broadly the tool can be applied and whether its use should be tailored to specific cases rather than implemented as a universal solution. Oncologists emphasized the importance of clearly defining the target population to ensure that the tool is used in situations where it genuinely adds value to clinical decision-making rather than introducing unnecessary complexity or misinterpretation.

Table 3.4 Quotes relevant to Perceived Usefulness

Subtheme	*Relevant Quotes*
Improved pain detection and monitoring	"I think that if you are better informed during the period between consultations, when you are not in contact with the patient, you could provide better assistance. [...] I believe you could certainly identify a group of patients that you are currently missing." - O11 "A lot of the decisions we make now are based on interval anamnesis. If, in advance, you could see how things have been going over time, without having to ask the patient, 'Did you have pain on Friday? And on Saturday? And what about last Sunday afternoon?', then I think this would be useful. It would be minimally burdensome for the patient and informative for me, particularly in helping to identify trends."- O08 "In an outpatient setting, this provides a lot of information that we wouldn't normally have, so I think there is great added value there." - O06 "I think you actually need some kind of alert system so that we don't miss severe issues. And who knows, maybe with such an alert system, we could intervene earlier in critical situations." - O03 "The patient population I see often has pain, particularly bone pain. In those cases, this tool could be quite helpful in detecting early signs that something is going wrong, something we might not have expected. So in that sense, I can see how this could enable earlier intervention." - O01 "If the trend clearly shows what has been happening, whether or not due to a change in intervention, then that would trigger me more than just a single momentary measurement. Patients often come to me and say, 'Well, doctor, I feel fine now.' But if I could see that over the past days their pain had only been increasing, I would interpret that very differently than if I saw their pain had consistently remained at a 0 or 1, in which case I would assume things are stable." - O08
Improved pain communication	"It acts as a kind of trigger to bring up the topic of pain more often, so I think it would reduce the number of times patients experience pain at home without us ever hearing about it in the consultation room." - O10 "I think it might make it easier to initiate conversations with the patient. You could say, 'I see that your pain scores have been increasing—does that match your experience? How are you feeling?' It would replace the need to explicitly ask the same question every time." – O07 "It is possible that this tool could prompt more frequent discussions about pain problems. In that sense, it could serve as a supportive tool for conversations between doctors and patients." - O02
Enhanced pain assessment consistency	"This [the tool] can provide more information, which could open the door to reducing the subjectivity of pain assessments." - O10 "Clinically, it might help relieve the burden on nurses. But in a hospital setting, I think the greatest added value is continuity. You often have multiple nurse shifts per day and different nurses throughout the week, so there is rarely the same nurse assessing pain consistently. In that sense, it could be very beneficial for maintaining continuity in care." - O06 "It could help address the challenge of obtaining an objective pain score, where one patient might rate their pain as a 7 and another as a 3, even though, as a healthcare provider, you have the strong impression that their pain levels are actually similar. The variability in scoring is so significant that an AI model that removes subjectivity could be very helpful. It could also help within individual patients—if the model is well-calibrated for that specific patient, then it could provide a more objective indication of whether their pain is improving or worsening. It would give us a more reliable way to determine whether things are getting better or not." - O04
Enhanced patient-engagement	"Patients could become more aware of their pain management. They could actively engage with it, pay more attention to it, and I think that could certainly play a role in the future." - O07

	"I strongly believe in giving control back to the patient whenever possible, and this tool contributes to that. Patients can see their own data and respond to it. In the sense of 'measuring is knowing,' I think this could be educational for patients." - O03 "From a broader perspective, you could see this as the beginning of self-reporting, something that could be expanded in many other ways." - O08
Conditions and barriers to usefulness	"I don't know [how useful this tool would be]. It depends—if it turns out to be a very good pain monitoring tool, and we can identify more patients with inadequately treated pain, then it could be highly beneficial. But that all depends on the tool's performance." – O09 "If the performance is good, and it achieves its intended goal, then it would be an advantage for patients."– O02 "I think if it were expanded beyond just assessing pain itself—because that's the challenge of pain objectivity—and instead incorporated additional metrics, like a step counter to track reduced movement due to pain, then it could become a much more valuable tool. It would be more than just pain assessment; it would be a pain-driven quality-of-life measure, making it more useful for clinical decision-making than a standalone pain score." - O07 "I will always call patients to ask, 'How are you?' So, you asked earlier, 'Is this a supplement or a replacement?' It is a supplement. You always have to ask, 'Was this an incidental occurrence? Do you experience pain more frequently?' It always comes back to the anamnesis." – O01 "Yes, maybe as a kind of replacement for the pain score, which would then become more reliable and objective." – O04 "Ultimately, you still need to have the conversation with the patient. There are many factors to consider: How is the patient doing overall? What pain medication are they using? How does that correlate with the data from the app? That's a key issue. How do you factor in medication use when interpreting the pain scores? This tool should serve as a starting point for that conversation, not a replacement for it." - O09 "I think in a clinical setting, it would play a lesser role because, essentially, the app does what a nurse already does—assessing pain based on all available observations. At home, where there is no nurse, it could add value. But in a hospital setting, if the patient is awake and responsive, I don't think it would provide much additional information beyond what we already gather from our clinical assessment and what the patient reports."- O07 "I think there will always be patients who simply don't engage with this kind of tool. Some people are resistant to using technology like this, or they may not see its value in their daily lives." - O11

3.4.5.2 Perceived Ease of Use

Perceived ease of use refers to how effortless oncologists and patients believe the AI-based pain assessment tool will be to use. During the interviews, oncologists assessed usability from both the patient's perspective and their own. Before discussing their own experience, they first described how they envisioned the tool's implementation in clinical practice. By leaving the implementation open-ended, the interviewer allowed oncologists to express their expectations about its integration.

The feedback on the perceived ease of use was categorized into four subthemes: 1) intuitive and simple interface and task for patients, 2) factors influencing patient usability, 3) integration with current systems, 4) presentation and interpretation of the outcomes. Quotes relevant to the perceived ease of use are presented in Table 3.5.

Ease of use for patients

Oncologists generally agreed that the presented prototype of the application was considered intuitive, simple and easy to understand for the patient. Several compared it to everyday digital

interactions, such as taking a selfie or using an app, which are already familiar to most people. They noted that opening an app, reading a short sentence, or recording a video are relatively low-threshold tasks, making the tool accessible to a wide range of users.

Despite the tool's intuitive design, oncologists identified several moderating factors that could affect its ease of use for different patient groups: 1) familiarity with technology: Patients with higher digital literacy would likely find the tool easier to use, whereas older patients or those with limited experience with smartphones may struggle, 2) physical and cognitive limitations: Patients experiencing severe pain, fatigue, or cognitive impairments due to cancer treatment might have difficulty using the tool consistently, and 3) device and financial access: Not all patients may own a smartphone capable of running the app, potentially limiting adoption in certain populations. These factors suggest that while the tool is designed to be intuitive, some patient groups may require additional support or alternative methods to ensure accessibility. Additionally, oncologists noted that some patients may perceive the tool as unnatural or unnecessary, affecting their willingness to use it. One oncologist (O04) pointed out that talking to an app about pain might feel unfamiliar or uncomfortable for some patients, potentially reducing engagement.

These concerns suggest that while the tool is designed to be intuitive, individual patient characteristics – such as comfort with technology, pain severity, and perception of necessity – could influence engagement and adoption. To ensure accessibility for a diverse patient population, additional support strategies or alternative approaches may be needed.

Ease of use for oncologists

For oncologists, ease of use was closely tied to how well the tool integrates into their existing clinical workflows. When asked whether the oncologist thought it was easy to integrate the tool outcomes into their clinical practices, all but two (O04 and O09) believed that seamless integration would be feasible. However, they emphasized that the outcomes of the tool must be easy to access without creating additional administrative burden. Key considerations for integration included: 1) seamless connection with electronic medical records so oncologists do not have to use separate platforms to retrieve pain assessments, and 2) automatic notifications or alerts when a patient's pain reaches a concerning threshold, rather than requiring oncologists to manually search for the data. One oncologist (O04) expressed frustration with previous attempts to integrate digital tools into their workflows, citing slow-loading systems and excessive manual input requirements as barriers to adoption. This highlights that even if a tool is clinically promising, its real-world usefulness will depend on how well it fits into existing systems and time-pressured workflows.

Another critical aspect of ease of use for oncologists was how the AI-generated pain assessments are presented and could be interpreted. Oncologists emphasized that the tool should provide clear, actionable insights rather than complex or ambiguous data. Preferred formats included: 1) a simple score or categorization that aligns with existing pain assessment methods, 2) graphical visualization of pain trends, similar to how blood test results are reported, allowing oncologists to assess a patients' pain trajectory at a glance, and 3) a one-sentence summary integrated into the EMR. Oncologists stressed that if the tool presents too much raw AI-generated data without clear interpretation, it could lead to confusion or yet another component to considered rather than

Table 3.5 Quotes relevant to Perceived Ease of Use

Subtheme	*Relevant Quotes*
Intuitive and simple interface and task for the patient	"In principle [I think the app is easy to use], yes. I mean, if we compare it to things we do daily with our phones, like taking a selfie or whatever? We're all used to that, so I think opening an app and doing something in it is quite accessible."- O01 "When I quickly look at the video, in essence, you're just doing this [Oncologist holds phone in selfie position]. How many people take selfies in a day? 'Good afternoon. I'm going to talk about my pain now.' They first read this text, yes, you need to focus for a moment. But if it means you can advocate better for your own situation, I think this is accessible enough for anyone to use effectively." – O08
Factors influencing patient usability	"If I were a patient, I think it would feel very unnatural, very strange, to talk to my phone. I would already feel a barrier, and I'm not even sick. If I were seriously ill in bed, I think it would be a significant hurdle to have to read a long sentence aloud like 'Lydia, who...', that seems difficult to me. And even harder to verbally describe my pain to a phone." – O04 "If someone is technologically literate, then yes. But when I see how precisely you need to look into the camera, I think it might not work well at the moments when you actually want to measure pain, because you might miss those critical moments." – O10 "Someone experiencing a real pain crisis is definitely not going to use an app and read a text aloud. I don't believe that at all. [...] I wonder if they would even be capable of doing it." – O09 "How well patients can use such an application also depends on their age, their level of digital literacy, and whether they even have a device capable of running the app. There could also be financial limitations." – O02 "If people are in pain while they need to move around, then that's not the moment they'll want to pick up their phone. If they're in pain multiple times a day, they'll experience the pain regardless of whether they report it. I think that because the tool samples at certain moments, you end up capturing only the moments when things are relatively okay, so I'd be concerned about sampling error and drawing conclusions that you could just as easily get from talking to the patient." - O10
Integration into current workflows and systems	"If you simply receive the results via email, then I don't see much difference between getting a lab result or getting a tool-generated result." – O01 "For me, it is essential that this is integrated into HIX [the EMR system used in the EMC] . I don't want to have to use a second, third, or fourth system just to access this data. If this is to be truly useful, then it must be integrated into HIX." – O08 "This [information from the tool] is, with all due respect, yet another piece of data added to the overwhelming amount we already receive. [...] If this happens, I would want active notifications rather than having to sift through half the patient file to see if they used the tool. I would mainly want to receive alerts if a certain threshold is exceeded—if there is a reason for concern. And ideally, you'd get those notifications in real time, not just when preparing for a consultation." – O09 "I think this is going to be difficult. As soon as it takes longer than simply asking, 'Do you have pain?' and 'What is your pain score?', then it becomes a problem for doctors. [...] If opening the tool in HIX takes even 10 seconds to load, then I'm not going to use it. [...] Right now, I just ask, 'Do you have pain?' and 'Can you rate it?' If this takes longer than that, it's going to be very difficult to integrate into daily practice." – O04
Presentation and interpretation of the outcomes	"If it's a simple score, then why not? I don't think it should be too complicated, but you do have to make sure that all the information leads to something that is easy to interpret. The tool analyses who knows how many different factors, but in the end, it needs to produce a clear score." O01 "I think a graphical representation would always be best—something where you can immediately see what's going on at a glance." – O09 "If there is a well-designed interface that allows for a one-sentence summary in the medical record, then yes, I would use it. We check blood test results every week, so if we can translate this into similar kinds of values, then I think we should assess it in the same way." – O10

support clinical decision-making. One oncologist (O01 added that the ability to interpret such data would likely improve over time, as clinicians become more familiar with the tool and its outputs.

3.4.5.3 Perceived Risks

The theme of perceived risks relates to the participant's perception of uncertainty and potential negative consequences associated with using the AI-based pain assessment tool. Participants were asked: "What concerns or risks do you see in integrating such a tool into current clinical practice?" Their responses highlighted concerns regarding four subthemes: 1) working mechanism concerns, 2) workflow disruption and increased workload, 3) privacy and data security concerns, and 4) negative impact on the patient-oncologist relationship. Quotes relevant to perceived risks are presented in Table 3.6.

A core tension centred around the tool's working mechanisms and epistemic limitations. Oncologists expressed scepticism about whether a system based solely on facial expressions and vocal cues could validly capture something as nuanced and multifaceted as pain. They questioned whether the tool would measure pain itself or instead infer related states such as discomfort, distress, or fatigue – experiences that are closely linked to pain but not necessarily equivalent. This reflected a broader uncertainty about whether an algorithm could meaningfully interpret pain across different individuals, especially given known variations in how pain is expressed culturally, psychologically, or due to illness. Some oncologists noted that patients who internalise their discomfort may be overlooked by a model trained on more expressive patterns. Others raised concerns about potential bias in the recordings, particularly if patients are more likely to use the tool during moments of intense pain, or about the possibility of unintentional or intentional manipulation of pain expressions. These uncertainties contributed to a cautious attitude toward the tool's reliability. Rather than rejecting the concept entirely, oncologists emphasised the importance of contextual information and clinical interpretation to complement any AI-generated assessment, suggesting that the tool's role would need to be clearly defined and carefully integrated into existing clinical judgement.

Another major concern among oncologists was that the tool could increase workload rather than reduce it. Many feared that managing additional data, handling notifications, and explaining the tool to patients would add to their administrative burden. Two oncologists (O04 and O09) explicitly questioned who would be responsible for processing AI-generated pain assessments. While some acknowledged that it is essential to act on the data collected, they feared that this responsibility would fall entirely on them. Some oncologists (O02, O07, and O11) suggested that a nurse or supportive co-worker could triage the results and escalate cases when necessary. However, given existing staff shortages, most oncologists preferred a system that only notifies them when a specific threshold is reached. Despite this, many oncologists worried that the tool could generate an excessive number of alerts, including pain scores that do not require immediate intervention, ultimately adding to rather than streamlining workload. If this were the case, they feared that using the tool could become more time-consuming than simply asking the patient about their pain during consultations, making its use impractical and potentially outweighing its intended benefits or even creating the risk of overtreating pain that would have been solved by

Table 3.6 Quotes relevant to Perceived Risks

Subtheme	*Relevant Quotes*
Working mechanisms concerns	"Can a computer really read from your face how much pain you are in, considering what I just mentioned—that we see so much variation? What a patient experiences and what is externally visible don't always align, and how they rate their pain can differ significantly." – O04 "Are you actually measuring pain, or are you measuring, I don't know, overall well-being? How do you know if you're detecting pain and not just a general sense of discomfort? I'm not sure if the system can distinguish between the two effectively. Those things are very closely related, so I find that quite concerning." – O09 "I can imagine that if you, you know, to make your plea, you could manipulate it. Patients can manipulate me as a doctor too, but they could record something that, quite literally and figuratively, does not reflect what they are actually feeling. So the possibility of manipulation cannot be ruled out." – O08 "I think there's a risk of bias, simply because awareness of pain is heightened when you open the app. If people only use the app when their pain is severe, then you're going to get a skewed dataset. I don't know exactly how it works in detail, but if only people with high pain levels are using it, you end up with a dataset that is shifted compared to normal conditions." – O07
Workflow disruption and increased workload	"We would be setting up a system where doctors get alerts whenever someone at home uses the pain app and reports higher pain levels. Then we face the issue of who is supposed to handle all those notifications? Who is going to go through all those signals from the computer? Who will call all those patients back? And of course, there's the risk of getting way too many alerts, because people—well, people experience pain. That could quickly become unmanageable in an outpatient setting." – O04 "Who is going to process all these notifications? I have serious concerns about that. You need healthcare providers to handle them. If you start measuring something, then you have to do something with that data—at least, that's my opinion. [...] So I see this as a major challenge, and in fact, I think it's the biggest challenge of all." – O09 "Ultimately, I want to know how my patients are doing. But no, I don't want more emails and phone calls—I just can't handle any more. If I'm going to receive reports, it really needs to go through another person, some kind of intermediary, where triage happens, just like it does now when patients call with complaints. Only the truly important cases should reach me." – O02 "Ideally, I would only receive the data when I choose to access it. The reality is that in a centre like this, we are bombarded with new tools that could potentially work very well, but in the end, they create more work. Maybe it leads to better care—because otherwise, these patients would just be sitting at home in pain, and that's not good either. But we don't have the time to solve all the problems for all patients. [...] We simply cannot handle that kind of signalling system in a healthcare system that is already short on personnel, where every day we're struggling just to get through our essential tasks." – O04 "It leads to a bit of over-hospitalisation of the patient. I think this adds another level to what we already do. I don't mean it to sound harsh, but there's a slightly paternalistic element to all of this—where we feel the need to take over everything and evaluate everything. And sometimes, I think decisions are made that aren't really necessary, or where additional pain treatment doesn't actually provide any benefit to the patient." – O10
Data security and privacy	"Privacy is a general concern, but of course, that's something we always need to consider." – O08 "There's also the general unease in society about using artificial intelligence in healthcare. People are hesitant because of the fear that data might end up being exposed." – O02
Negative impact on patient-oncologists relationship	"Essentially, we are all looking for more objective measures to properly assess a patient's pain experience. On one hand, that can be a great thing. But on the other hand, it risks creating a dynamic based on distrust. And that should never be the emotion that comes out of something like this. You don't want it to feel like, 'Just tell the machine, so the doctor doesn't have to discuss it with you anymore, and they'll just prescribe a pill.' That's not the kind of interaction I want." – O08 "You have to be careful that you don't turn into some kind of Inspector Morse, where you say, 'See, you're not telling the truth at all.' That would be incredibly condescending, and that makes it tricky." – O08 "I don't know if, maybe, if this replaces some patient interactions or activities, then you already start to lose that connection. It risks making everything more robotic." – O06

itself. To mitigate this risk, oncologists emphasized that the tool must integrate seamlessly into clinical workflows, avoid creating excessive administrative burden and have a measure that would help decide whether action is really needed.

Additionally, five oncologists (O02, O05, O07, O08, O11) mentioned the importance of data security and privacy. The use of facial expressions and vocal cues for pain assessment introduces sensitive data that must be handled with strict safeguards to prevent misuse and maintain patient trust. While oncologists acknowledged the need for secure data storage, restricted access, and clear policies on data usage, these concerns were not explored in depth during the interviews, as the discussion remained at a general level rather than addressing specific security measures or regulatory frameworks.

A more subtle, but deeply meaningful concern raised two oncologists (O06 and O08) related to the potential negative impact of using this tool on patient-oncologist relationship. They cautioned that if the AI-based pain assessment were to substitute rather than supplement direct interactions, it could risk depersonalising care. The oncologists worried that patients might feel reduced to data points – as though they were reporting their pain to a machine, rather than being heard by a clinician. While objectivity and efficiency were perceived as potential benefits of the tool, the relational dimension of care – the feeling of being seen, heard, and taken seriously – remains central to pain management, particularly in oncology. From this perspective, the risk is not only that the tool could disrupt the flow of communication, but that it might unintentionally signal distrust or disinterest. These reflections highlight the importance of positioning this concept as a supportive tool within the therapeutic relationship – one that enhances, rather than replaces, interpersonal engagement.

3.4.5.4 Trust

The construct of trust was defined as the participant's belief that the system will operate responsibly, fairly, and without exploiting the vulnerabilities of patients or clinicians. Participants were asked whether they would trust the tool and its outcomes. While trust is considered a key determinant in the adoption of new technologies in the mTAM model, oncologists in this study did not perceive it as an independent factor influencing their willingness to use the AI-based pain assessment tool. Trust in the tool was seen as conditional, requiring: 1) scientific validation, 2) experience in practice, and 3) confirmation from the patient, before they would feel confident in its assessments. Table 3.7 shows the quotes relevant to trust.

These findings suggest that trust does not function as a standalone predictor of adoption but rather as a moderator that influences oncologists' perceptions of usefulness and risk. Oncologists were not inherently distrustful of AI-based pain assessment but rather conditioned their trust on validation and personal experience. If scientific evidence confirms the tool's accuracy, oncologists would be more likely to perceive it as useful and adopt it in practice. If the tool proves unreliable or inconsistent, trust would decline, reinforcing concerns about risks and potential misinterpretation of pain.

Table 3.7 Quotes relevant to Trust

Subtheme	*Relevant Quotes*
Trust requires scientific validation	"If the research outcomes are valid and the performance proves to be good, then yes." – O02 "Not directly. [...] For me, this very much depends on the study design, as we just discussed." – O03 "I would really like to see the tool's performance in a study. Only then would I trust it. So I need a well-designed study and results proving that it works." – O06
Trust requires experience with it in practice	"Yes, I think that ultimately, if you see that it aligns very well or that it helps, then yes. I think, in the end, reality and how you experience it will determine trust."– O05 "I think I would first need to experience it. Trust wouldn't be gained immediately." – O11
Trust requires confirmation from the patient and other factors	"I think it would take a very long time before I would trust it completely. That naturally takes time. And even if you gain good experience with it over time, you would still always ask the patient, 'Do you think this result is accurate?'" – O04 "I trust it just as little as I trust what patients say themselves—it is just one part of a much bigger conversation, not a standalone decision." – O10

3.4.5.5 Behavioural Intention

Behavioural intention refers to the likelihood that oncologists would use the AI-based pain assessment tool if it were available in clinical practice. Oncologists were asked how likely they would be to adopt the tool and under what conditions they would consider implementing and continuing to use it. Their responses varied, reflecting a mix of openness to experimentation and conditional willingness based on scientific validation and perception of ease of use and handling of the perceived risks. Quotes relevant to behavioural intention are shown in Table 3.8.

Several oncologists expressed a willingness to experiment with the tool if it became available, particularly out of curiosity and to assess its potential impact. O07 stated that they would immediately start using it, but mainly to explore its functionalities rather than with a clear expectation of clinical benefit. Similarly, O01 compared adopting the tool to integrating a new lab test—suggesting that, as with any new diagnostic method, clinicians would gradually experiment with it in selected cases before implementing it more broadly. This indicates that while oncologists are not immediately committed to using the tool long-term, but that they are interested and open to testing it in real-world settings.

The strongest determinant of intention to use the tool was scientific validation. Oncologists were generally unwilling to integrate the tool into routine practice unless it was rigorously tested and proven to be reliable and effective. O02, O03 and O04 explicitly stated that their willingness to use the tool depended on whether research demonstrated its accuracy and clinical value. These responses highlight a cautious but science-driven approach to technology adoption. Oncologists are not resistant to AI-based tools, but they require strong clinical evidence before integrating them into their practice.

Beyond scientific validation, oncologists emphasized that practical feasibility would also determine whether they would actually use the tool. Ease of use and overcoming perceived risks were key concerns for O05, O06, O08 and O09.

Interestingly, while many oncologists expressed conditional willingness to use the tool, one oncologist (O07) noted that they do not feel an urgent need for such a solution. This suggests

Table 3.8 Quotes relevant to Behavioural Intention

Subtheme	*Relevant Quotes*
Openness to experimentation	"I think that if it's available, I would immediately start using it, but mainly out of curiosity and to experiment with it—to see what it can do. In the long run, though, for me, it ultimately comes down to 'How much impact does this pain have on the patient?' And so far, that hasn't really been clear." – O07 "I think that if there is good data showing that this tool is helpful, then I would experiment with it. It's similar to, well, I can't think of many other examples, but it's like when we get a new lab test. You might think, 'Let's try this with this patient,' and then you gradually start selecting who it is and isn't suitable for. You experiment a little to see where it works, and then you apply it more broadly." – O01
Conditionally willing based on scientific validation	"If it has been validated, works well, and is reliable, then I would use it." – O02 "Well, I am a critical scientist, so if I am convinced that it provides meaningful measurements, then I would be very enthusiastic about implementing it because I see a lot of potential benefits. I would definitely participate in research on it, and if I ultimately see that it has added value and that patients are motivated and benefit from it, then I would certainly use it." – O03 "If it is evidence-based, then yes, I would use it." – O04
Conditionally willing based on feasibility and overcoming risks	"It depends on how easy it is for us to use." – O05 "If it works well and doesn't add too much workload [...] then yes. If it's feasible in practice, I think it would be interesting to try." – O06 "If I can just instruct a patient to use it at certain times—something like, 'Just press the button five times a day for a few days before your appointment, and I can see the results'—then I think I could implement it easily. At my age, I'm still a little curious about these things."– O08 "Well, I think it's likely, because I'm part of the palliative care team, and I see a lot of patients, so I think I would cooperate with it. But at the same time, I wonder, 'How exactly would that work?'" – O09
Lack of perceived need for the tool	"Look, if it's available, I might be interested in using it, but only if it's readily accessible in the hospital. If it isn't, I don't think I would actively seek it out because, for me, I don't currently see a major gap in how we assess pain." – O07

that some oncologists may not perceive a strong need for AI-based pain assessment, particularly if they feel that current methods are sufficient. This lack of urgency may be a barrier to widespread adoption.

Overall, oncologists' intention to use the AI-based pain assessment tool was largely conditional, shaped by the need for scientific validation, ease of use, and perceived clinical value. Their attitude can be described as cautiously interested – open to exploring the tool's potential but sceptical about its working mechanisms, immediate usefulness and integration into routine practice.

3.4.6 Design and Implementation Preferences

In the final part of the interviews with the oncologists, questions were asked related to the design and implementation preferences regarding the tool. Their responses highlighted both essential technical and practical requirements for successful adoption and additional features that could enhance the tool's usability and impact. Five key themes were identified: 1) accessibility, 2) graphical representations, 3) notification preferences, 4) capturing additional contextual information, 5) providing clinical advice. Additional information on these themes could be found in Appendix H.

3.5 Discussion

This study explored oncologists' perspectives on cancer pain assessment and their attitudes towards the initial concept of an AI-based automatic pain assessment tool. The interviews identified five interrelated themes that reflect the challenges in current pain assessment: 1) the subjective and multidimensional nature of pain; 2) ethical tensions around responsibility for pain management; 3) barriers in the communication and interpretation of pain; 4) challenges in clinical decision-making; 5) the practical constraints imposed by time, continuity and care context. Together these themes form a broader conceptual understanding of the oncologist's role in pain assessment and the structural and fundamental limitations of current practices. It illustrated that pain assessment is not merely a clinical measurement task, but rather a dynamic, interactive, and ethically layered process shaped by personal, relational, and systemic factors.

3.5.1 Current challenges

Oncologists consistently recognised pain as more than a physiological symptom. Instead, they viewed it as a lived experience, shaped by emotional, cognitive, and cultural factors. This aligns with longstanding understandings of Melzack et al. [170] of pain as a multidimensional phenomenon, and more recent work emphasising the importance of incorporating patients' narratives into assessment, instead of focusing solely on symptom measurement [171]. In clinical practice, however, this understanding often collides with the use of standardised pain scores, which may reduce pain to a single dimension of intensity. Several oncologists described the difficulty of assessing the severity or impact of pain without losing sight of the broader person behind the score. These findings underscore the need for pain assessment methods that can reflect pain's emotional, social, and existential dimensions – particularly in cancer care, where pain is often entangled with uncertainty, fear, and personal reflections about illness and the future.

Additionally, a central tension identified by participants was the question of who "owns" the pain problem – the patient, the oncologist, or the broader care team. While oncologists generally agreed that pain is ultimately the patient's experience, they differed in how much responsibility they felt for actively initiating pain discussions. Many expressed the expectation and encouragement that patients would report pain themselves, reflecting broader trends in oncology toward patient self-management [172] and shared decision-making [173]. While this approach supports autonomy and personalised care, it can also risk shifting the burden of responsibility onto patients – particularly in settings where pain is under-recognised or inadequately managed. Some oncologists acknowledged this risk and pointed to structural blind spots in routine pain assessment, while others believed that only a small number of cases go unnoticed. However, this belief is not fully consistent with research showing that more than a third of cancer patients continue to experience moderate to severe pain [13], suggesting that missed pain remains a significant issue and that greater awareness and education may be needed. This ethical dilemma – relying on patients to initiate pain discussions versus proactively addressing pain – remains unresolved. Oncologists in this study attempted to lower the threshold for communication by creating a safe space for patients to raise concerns, yet some questioned whether this was sufficient. Stigma, fears surrounding medication use, and the belief that pain is simply part of

having cancer may still prevent patients from speaking up. Similar concerns have been reported in a recent qualitative study where cancer patients expressed uncertainty about who was responsible for managing their pain, and a sense of being let down by the healthcare system when no one took ownership of their pain management [174]. This suggests that the dilemma is felt on both sides of the care relationship. A parallel challenge has also been described in chronic pain care, where "the challenge faced by healthcare providers during encounters with patients with chronic pain is described by the incompatible requirements of empowering patients while maintaining a professional perspective to avoid disempowering themselves" [175]. Together, these findings underline the need for clearer structures, shared expectations, and potentially new tools that support both patients and clinicians in collaboratively addressing cancer-related pain. Further research is needed to explore how oncologists can take a more proactive role in pain management without undermining patient autonomy.

Communication and interpretation of pain emerged as a deeply intertwined challenge in pain assessment. Oncologists in this study described not only the difficulty of eliciting clear information about pain but also the complexity of interpreting how it is expressed. Many patients reportedly struggled to verbalise their pain, downplayed their symptoms, or provided descriptions that felt vague or inconsistent over time. These challenges align with established patient-related barriers in the literature, such as underreporting due to stigma, uncertainty, or difficulty finding the right words to describe the pain experience [11, 128, 176, 177]. As a result, interpreting these expressions required oncologists in this study also to rely on their own clinical intuition, non-verbal cues, and contextual information. While the role of non-verbal pain expressiveness in influencing clinician judgement has been reported in studies examining the effect of non-verbal expressiveness of pain [178], this study is, to my knowledge, among the first to qualitatively highlight how oncologists actively draw on such cues during routine cancer care. This reliance on implicit interpretation reveals the interpretive nature of pain assessment – where understanding pain is not simply a matter of collecting data, but of reading between the lines in emotionally and relationally complex encounters. It also raises concerns about potential misinterpretation, particularly when communicative barriers are encountered, and non-verbal expressiveness is low or culturally modulated. In this light, the findings point to the importance of supporting both clearer patient expression and more consistent clinician interpretation – both of which were also identified by oncologists as key areas for improvement in the current pain assessment process.

Beyond communication and interpretation, a distinct challenge reported by oncologists was the complexity of clinical decision-making in response to pain assessments. Pain management was not described as a linear or strictly protocol-driven process, but rather as a nuanced balancing act. While pain relief remains a central goal, decisions about interventions are shaped by feasibility, patient preferences, anticipated side effects, and the broader context of cancer treatment. Several oncologists noted that the goal is often not complete pain elimination, but achieving a level of pain that is tolerable and compatible with the patient's desired quality of life. This perspective aligns with current clinical guidelines that encourage a careful, individualised approach to pain assessment and management [179]. Although participants stressed the importance of assessing pain in relation to a patient's coping capacity, functional status, and personal values, their reflections also indicate a need for clearer guidance on how to integrate these dimensions into

clinical decision-making – particularly in situations where patient-reported experiences conflict with clinical observations, or where treatment options are constrained. In this context, tools like the NRS offer a standardised way to quantify pain and are sometimes linked to treatment protocols. However, oncologists in this study described using pain scores primarily to monitor trends within a patient over time, rather than as reliable cross-patient benchmarks or direct indicators for action. They emphasised that the NRS does not reflect tolerability, the functional impact of pain, or individual variability in pain expression. This aligns with concerns in the literature about the limitations of numeric scores in guiding nuanced pain management decisions, particularly in complex cancer care [180]. Taken together, these findings highlight the need for decision-support approaches that move beyond numeric thresholds and better account for the full clinical and personal context in which pain decisions are made.

Lastly, this study highlights broader structural challenges in oncology care. Time constraints, staff shortages, and disruptions in continuity of care were reported as significant barriers to consistent pain assessment. These challenges are widely documented in the literature [181] and align with the increasing pressure on healthcare systems, which has been linked to fragmented care and reduced clinician capacity to address symptom management comprehensively. Oncologists in this study reported that they often have to prioritise topics during consultations, with pain assessment not always taking precedence – despite hospital protocols and clinical guidelines advocating for pain to be assessed at every visit [182]. These challenges are especially pronounced in the outpatient setting, where clinicians have limited visibility into patients' experiences between visits. Without systems for longitudinal pain monitoring, changes in symptoms or responses to treatment may go undetected, limiting timely intervention. This lack of monitoring has also been identified in literature as a barrier to adequate outpatient pain management [183]. Together, these findings underscore the need for solutions that enable more continuous monitoring and ensure that pain remains a central focus of care, even in resource-constrained settings.

3.5.2 Acceptance of the AI-based Pain Assessment Tool

In this context of experienced challenges, the second part of this study examined oncologists' attitudes towards the initial concept of an AI-based automatic cancer pain assessment tool, guided by the mTAM framework, assessing perceptions of usefulness, ease of use, risks, trust, and behavioural intention.

Oncologists generally recognised that the AI tool could offer valuable support in addressing existing pain assessment challenges – particularly in the outpatient setting, where continuity of symptom monitoring remains difficult. They perceived the tool as potentially beneficial in identifying unreported pain, monitoring trends over time, improving communication, and enhancing consistency across assessments. These perceived benefits align with the well-established challenges in cancer pain management of the first part of this study. The tool's capacity to provide longitudinal pain data was seen as a particular strength, supporting calls for dynamic pain monitoring approaches that move beyond single-point self-reports [184]. These perceived benefits show the tool's potential to complement and enhance clinical decision-making.

Despite this cautious optimism, acceptance of the tool was highly conditional. Across interviews, scientific validation emerged as a key prerequisite. Oncologists emphasised that the tool must be proven to be accurate, reliable, and clinically meaningful before they could incorporate it into decision-making. This reflects a broader evidence-based ethos within clinical practice, where new technologies are met with cautious interest rather than immediate enthusiasm. As highlighted in the Topol Review [185], digital healthcare technologies hold great promise for improving diagnostic accuracy, efficiency, and clinician workflow, but their implementation "must only be carried out when there has been robust clinical validation." The alignment between these policy-level insights and oncologists' views in this study underscores the importance of transparent validation and careful integration of AI tools into real-world practice. For developers, this finding reinforces the importance of prioritising transparency and performance validation as part of the development process, particularly across diverse patient populations and clinical settings.

Beyond validation, seamless integration into existing workflows was described as a prerequisite for use. Oncologists were pragmatic in their reflections, highlighting that even promising tools risk rejection if they increase workload or disrupt clinical routines. These concerns reflect broader findings on digital health adoption, where usability, interoperability, and time-efficiency consistently emerge as key factors for implementation success [186]. The idea that the tool should not introduce "yet another data stream" but instead offer actionable, synthesised insights is particularly relevant in light of the earlier identified challenges – specifically, the cognitive burden of balancing multiple inputs in pain assessment and the structural time limitations that often restrict the depth of pain discussions. This suggests that user-centred interface design and strong interoperability with EMR systems will be critical to ensure real-world feasibility. For example, a one-sentence trend summary (as suggested by several participants) or colour-coded alerts could enable fast interpretation without disrupting consultation flow.

A further insight was oncologists' concern that the current concept of the AI-based tool may oversimplify the complexity of pain by focussing too narrowly on intensity of expressed pain. Several oncologists warned that by reducing pain to a numeric trend or AI-generated score, the tool might misrepresent patients' lived experiences. This critique was also mentioned for the NRS-score in the first part of this study and echoes long-standing concerns in pain research about the limitations of quantitative pain scales [180]. To address this limitation, future iterations of the tool could consider incorporating indicators of pain-related distress, functional interference, or mood – elements recommended in multidimensional pain assessment frameworks like the Brief Pain Inventory [187]. Likewise, the tool could be expanded to recognise additional affective states, as facial expressions – composed of specific facial action units as described in FACS [70] – are known to convey a wide range of emotional experiences beyond pain [188].

In addition to concerns about conceptual scope, several oncologists raised more technical questions about how the AI model would interpret pain. Specifically, they expressed scepticism about the tool's reliance on facial expressions and vocal cues as proxies for pain intensity, highlighting individual variability in pain expressiveness and the risk of misinterpretation. Some oncologists noted that patients who internalise their discomfort, or who express pain in less conventional ways, may not be accurately represented by a model trained on generalised patterns.

This concern aligns with literature presenting that different 'faces of pain' exist [189, 190]. Moreover, oncologists questioned the underlying protocol for when patients would record their pain. If recordings are made primarily during moments of severe pain – or conversely, only when patients feel well enough to engage – the resulting data may be skewed, creating a biased picture of the patient's overall pain experience. This concern aligns with studies warning of "sampling bias" in ecological momentary assessment and digital health data collection [191]. These concerns suggest that careful attention must be paid to how, when, and in what context pain is measured and interpreted by the tool. For example, more passive or frequent sampling strategies could be explored, such as running facial analysis in the background when patients interact with their other healthcare-related applications (e.g., Digizorg), thereby reducing the burden of active input and capturing a broader range of expressions across different moments. Clarifying the tool's analytical focus and defining consistent measurement protocols will be critical next steps for the conceptualisation process to ultimately gain clinician confidence and ensuring fair, context-aware interpretation of AI-generated outcomes.

The findings suggest that oncologists' behavioural intention to use the AI-based pain assessment tool is best characterised as cautiously exploratory. While few oncologists envisioned immediate adoption, many expressed openness to testing the tool in practice, particularly to evaluate its added value for outpatient pain monitoring. This exploratory attitude aligns with broader patterns in digital health adoption, where clinicians may initially engage with novel tools on a trial basis before deciding whether to incorporate them more systematically [192]. The relatively low sense of urgency among some oncologists suggests that future adoption efforts should target settings where pain is currently under-monitored or difficult to assess. Demonstrating real added value – both in patient outcomes and clinician efficiency – will be essential to move from experimentation to sustained use.

In sum, this study highlights that for an AI-based pain assessment tool to be acceptable and valuable to oncologists, its development must align with their clinical logic and practical constraints. Key priorities include: ensuring robust scientific validation; designing for seamless workflow integration; expanding beyond unidimensional pain intensity; clarifying measurement protocols to reduce bias; and designing the interface around clinician interpretability. By embedding these insights into further development stages, the tool can be better tailored to address real-world pain assessment needs and support high-quality cancer care.

3.5.3 Limitations

While this study provides valuable insights into oncologists' perspectives on cancer pain assessment and AI-assisted pain evaluation, several limitations must be acknowledged. These limitations primarily relate to the study's sample size and composition, methodological constraints, and the evolving nature of AI in healthcare.

One of the primary limitations of this study is the exclusive focus on oncologists. While their perspectives provide valuable insights into the challenges of pain assessment and AI-assisted evaluation, the views of patients—the other key stakeholders in pain assessment—remain underexplored. Due to time constraints, patient interviews had not reached data saturation at the

time of analysis, limiting the extent to which their perspectives could be integrated into the findings. Additionally, while data saturation was achieved for oncologists, a larger and more diverse sample – including oncologists from different institutions and healthcare systems – could have provided a broader range of perspectives, potentially revealing variations in attitudes based on institutional resources, workflows, or regional differences in pain management practices. Another limitation is the absence of perspectives from other relevant healthcare professionals. As found during the interactions mapping of the pain assessment process, pain management is inherently multidisciplinary, often involving pain specialists, palliative care teams, and nurses. Insights from these professionals could provide a more comprehensive understanding of the current gaps in pain assessment and how AI-assisted tools might integrate into existing pain management strategies. Future studies should incorporate these perspectives to ensure a holistic evaluation of AI-based pain assessment in oncology care.

Besides this, the study relied on voluntary participation, which introduces the possibility of selection bias. Oncologists who chose to participate may have had a greater interest in pain management or digital health technologies, potentially influencing the findings toward more favourable or critical viewpoints. Conversely, oncologists who are less engaged in pain management or sceptical about digital health tools may have opted not to participate, meaning that some perspectives may be underrepresented. Similarly, social desirability bias cannot be ruled out, as participants may have provided responses that they believed were expected or aligned with best clinical practices rather than reflecting their actual day-to-day behaviours.

Next, the study employed semi-structured interviews, which offer depth and flexibility but also pose limitations in terms of standardisation and comparability. While the interview guide ensured coverage of key themes, the open-ended nature of the interviews meant that discussions varied between participants, potentially leading to differences in emphasis across interviews. Additionally, given that oncologists often faced time constraints, some interviews may have been shorter than ideal, potentially limiting the depth of discussion on complex topics such as ethical dilemmas in pain management or long-term AI adoption concerns.

Following on the methodological limitations, this study explored oncologists' hypothetical acceptance of an AI-based pain assessment tool rather than its actual implementation in practice. While oncologists provided thoughtful insights into potential benefits, risks, and barriers, their perspectives may change when using the tool in real-world clinical settings. Although the insights of this study could inform the development and design of the AI-based pain assessment tool, it must be kept in mind that oncologists' attitudes may evolve when the tool is actually developed.

Lastly, the use of the mTAM model in this study revealed some challenges in capturing distinct aspects of oncologists' acceptance of AI-assisted pain assessment. There was notable redundancy in responses, with oncologists frequently referring to their previous answers, suggesting overlap between the model's constructs. While risks associated with the technology were clearly identified, trust appeared to be more of an outcome of perceived risks and perceived usefulness rather than an independent construct influencing acceptance. This raises questions about whether mTAM is the most suitable framework for assessing oncologists' perspectives on such an AI tool in clinical practice. The model may be more applicable when evaluating patient acceptance, as their primary

focus would likely be on the technology as an mHealth tool for self-monitoring and communication, rather than its integration into clinical decision-making. Future studies should consider refining the framework or complementing it with additional theoretical models that better capture the complexities of AI adoption in medical practice.

3.5.4 Future Directions

Building on this study, several key steps are needed to further explore the feasibility and impact of AI-assisted pain assessment in oncology. Expanding the interview study to include patients and pain specialists, as well as oncologists from other institutions, would provide a more comprehensive understanding of diverse perspectives. Additionally, involving patients directly in the design and iterative testing of the prototype could offer valuable insights into user acceptance, usability, and potential barriers to engagement. To ensure clinical relevance, future research should focus on developing a clear integration concept for oncologists to evaluate, ensuring alignment with existing workflows.

Some oncologists in this study suggested exploring collaborations with existing initiatives that aim to capture multiple dimensions of pain beyond facial expressions and vocal cues. Integrating the AI tool into a broader, multimodal pain assessment framework – potentially combining patient-reported outcomes, physiological data, and behavioural indicators – could enhance its clinical utility and increase its chances of adoption. For the future development of the tool and the AI model, the insights from this study should be translated into specific, measurable, achievable, relevant, and testable (SMART) requirements. Doing so will support the conceptualisation of a workable and iterative concept that bridges the gap between current clinical challenges, technological potential, and practical application. Moreover, embedding these requirements into the next design phase – including decisions about measurement moments, interface design, data outputs, and EMR integration – will help ensure that the tool is perceived not just as innovative, but as usable, trustworthy, and aligned with oncologists' real-world workflow and reasoning.

Lastly, several oncologists in this study emphasised the importance of scientific validation and real-world testing to ensure that any AI-assisted solution is not only theoretically sound but also practically reliable. As such, future development should include clinical validation studies to evaluate the model's accuracy, reliability, and potential impact on pain management. In parallel, optimising workflow integration and implementation strategies will be essential to ensure that the tool supports, rather than disrupts, daily clinical practice.

3.6 Conclusion

This study explored oncologists' perspectives on cancer pain assessment and their attitudes toward an AI-based automatic pain assessment tool. The findings revealed five key challenges in current pain assessment: the subjective and multidimensional nature of pain, ethical dilemmas surrounding patient autonomy and professional responsibility, communication barriers in pain expression and interpretation, complex decision-making processes that integrate multiple clinical considerations, and contextual constraints such as time limitations and continuity of care issues.

These challenges do not exist in isolation but are deeply interconnected, shaping how oncologists assess and manage pain within the structural and epistemic limitations of clinical practice.

The results further highlight that oncologists recognise the need for improvements in pain assessment, particularly in outpatient settings where monitoring is less continuous. Their perspectives on the initial concept for an AI-assisted pain assessment reflected both interest and caution. Oncologists saw potential benefits, particularly in improving pain monitoring, enhancing communication, and addressing unreported pain. However, they emphasised the necessity of scientific validation, seamless integration into clinical workflows, and maintaining direct clinician-patient interactions to ensure meaningful adoption.

Beyond these attitudinal insights, the findings offer concrete directions for the ongoing conceptualisation of the AI-based pain assessment tool. Future development should prioritise multidimensionality, usability, and seamless integration, with clearly defined design and validation criteria aligned to clinical needs. This study underscores the importance of aligning technological innovation with real-world practice and clinical reasoning, ensuring that AI-driven tools enhance, rather than hinder, the quality of interaction and trust between clinicians and patients.

To increase feasibility and clinical value, further research should expand the range of perspectives included – particularly those of patients and pain specialists – and focus on the co-development and evaluation of the tool in real-world clinical settings. Ultimately, a user-centred and evidence-based approach will be key to realising the promise of AI-based APA in oncology.

3.7 Conflict of Interest and Funding

This study is part of the SENSAI project and was funded through a Starting Grant awarded to Dr. M. Mulder by the Dutch Ministry of Education, Culture and Science. The funding body had no role in the study design, data collection, analysis, interpretation, or writing of this report.

The author is involved in the design and development of the tool as part of her academic training and forthcoming PhD trajectory. This role is carried out within the scope of the SENSAI project and does not involve any financial interest or personal gain outside of the academic context. There are no commercial affiliations or financial relationships that could be perceived as a conflict of interest.

4 Conceptualisation

This chapter presents the conceptual framework for the AI-based APA tool, detailing its core functionalities, data collection approach, AI model processing, and feedback mechanisms for patients and oncologists. It describes the methodology behind its development, incorporating literature review, expert input, and insights from the exploratory interview study. The chapter outlines system workflows, design considerations, and the rationale for using a mobile application for data collection and a web-based platform for oncologist access. Additionally, it addresses technical feasibility, user experience, and ethical considerations, ensuring the tool aligns with clinical needs while maintaining security and usability.

4.1 Introduction

Currently, many cancer patients experience cancer-related pain [13], despite the availability of effective treatments [11]. To address this issue, improving pain management is essential. Accurate pain assessment is the cornerstone of such efforts [5]. Currently, oncologists face significant difficulties in assessing and managing cancer-related pain, as discussed in Chapter 3. To overcome these challenges, an innovative solution is needed.

Drawing from practical experience with the challenges of pain assessment in oncology, as well as an understanding of recent technological advancements and the believed potential for technology to address these issues, the idea emerged to develop an AI-based APA tool. Following an initial research phase that thoroughly explored and defined the current pain assessment challenges in oncological care, an initial concept for the tool was developed. The tool would collect audiovisual recordings of facial expressions and vocal cues, which an AI model would process to generate an automatic pain assessment. This assessment would be shared with both the patient and the

oncologist, with the goal of enhancing self-management and improving pain management strategies.

However, before progressing to full development, this initial concept must be further refined into a detailed and viable conceptual framework. To ensure the tool is both relevant and effective, and aligned with the needs of both patients and clinicians, a user-centred design approach is essential. This approach, informed by insights from end-users, ensures that the tool remains responsive to real-world needs and experiences. It also aligns with the recommendations from the Topol Review [185], which emphasizes keeping patients at the core of healthcare innovation. By integrating human-centred AI principles, the tool's design will better meet the needs of its users, improving both its acceptance and effectiveness.

Building on insights gained from the exploratory interview study (see Chapter 3) and the earlier performed literature review (see additional provided document), this chapter outlines the conceptualisation process and presents the development of the working concept for the AI-based APA tool. This conceptual framework forms the foundation for subsequent stages of application development, database structuring, and AI model training, ensuring that the tool aligns with clinical requirements and contributes meaningfully to the improvement of pain assessment in oncology.

4.2 Methodology

4.2.1 Concept Development Approach

The conceptualisation of the AI-based APA tool followed an iterative, evidence-based approach that integrated theoretical insights, clinical expertise, and technical feasibility considerations. The development approach for the concept, illustrated in Figure 16, consisted of two main phases. While the research phase primarily focused on defining the problem, as presented in Chapter 1, it also contributed to shaping the initial concept and is therefore briefly addressed in this chapter. To avoid redundancy, the emphasis is placed on the conceptualisation phase, which followed a structured process of diverging to explore various design possibilities before converging on a working concept, useable during the application development (Chapter 5), database development (Chapter 6) and AI-model development. This approach ensured that the tool was systematically refined to address the identified challenges effectively.

4.2.1.1 Research Phase

The development of the AI-based APA tool began with the initial idea of automating pain assessment in cancer patients. The initiator of the project (MM) identified challenges in the current pain assessment process and hypothesized that AI-driven automation could address these issues. To validate the relevance of this problem, an exploratory interview study with oncologists was conducted to identify existing challenges in pain assessment and management. This study confirmed that the difficulties perceived by the project initiator were shared by other healthcare professionals, reinforcing the need for an improved approach (see Chapter 3).

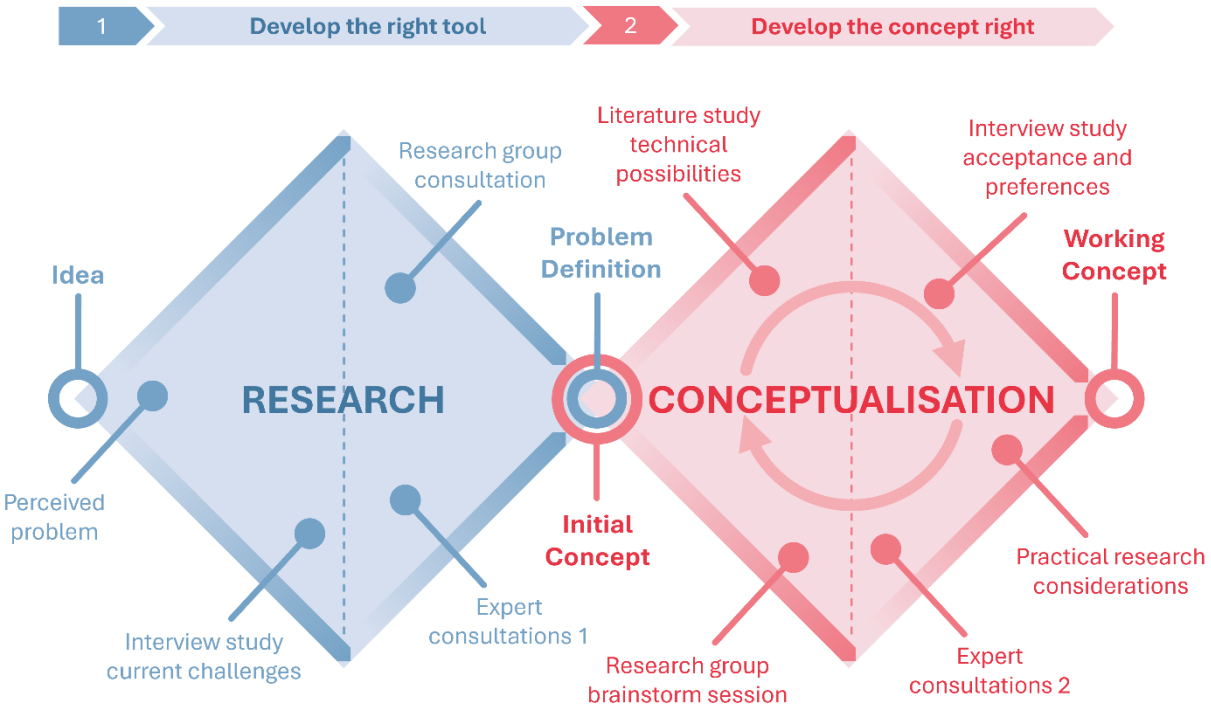

Figure 16 - Concept Development Approach

To further refine the initial idea, a dedicated research group was established, bringing together experts from medical (MM, CR, WO, MK), technical (HT, MK), and AI backgrounds (HT, DL). This group was consulted to gather insights, define the core challenges, and formulate an initial concept for the tool. Additionally, consultations with external experts were conducted to incorporate broader perspectives and expertise beyond the research team. An overview of the contacted experts is detailed in Appendix I. These consultations provided valuable input on current advancements in pain assessment, existing technological solutions, and best practices for developing and validating AI-driven healthcare applications. Their advice contributed to refining the problem scope, defining the research strategy and the initial concept.

4.2.1.2 Conceptualisation Phase

The conceptualisation phase aimed to refine the initial concept into a structured and feasible working concept by integrating insights from literature, expert consultations, and practical considerations.

To establish the technical feasibility and research foundations, a literature study was conducted to explore current advancements in AI-driven pain assessment, identify existing methodologies, and outline the technical requirements for AI model development. This study helped define key considerations for data collection, model architecture, and potential challenges in implementation.

Following this, a brainstorming session was organised with the research team, which included experts in AI (HT, DL), technical medicine (MK), and clinical oncology (MM). This 120-minute session focused on exploring end-user expectations, possible functionalities, technical feasibility, and research-oriented design decisions. To facilitate structured discussions, a Figma board was

prepared, which provided a visual representation of potential workflows and conceptual elements (see Appendix J).

To further refine the concept, a new round of expert consultations was conducted with specialists outside the core research team (see Appendix I). These sessions provided additional insights into best practices for AI-based medical applications, usability considerations, and potential clinical implementation pathways.

Additionally, the outcomes of the second part of the interview study (see Chapter 3) informed the conceptualisation process. This study assessed oncologists' acceptance of the concept, identified areas for improvement, and gathered their requirements and preferences concerning its functionality and integration into clinical workflows.

Finally, practical research considerations, such as data collection strategies, system usability, and technical and financial constraints, helped guide the convergence towards a working concept. This structured approach ensured that the AI-based APA tool was conceptually sound, technically feasible, and aligned with both clinical and research objectives.

4.2.2 Working Concept

Based on the conceptualisation process, a structured working concept was formulated. The first step in this process was defining the core functionalities of the tool – establishing what the tool will do.

Following the definition of core functionalities, the system workflow was developed to determine how the tool will operate in practice. This included conceptualising the interactions between the user, the AI model, and the feedback mechanisms, ensuring that the tool is both intuitive and efficient. The workflow was designed to integrate seamlessly into the patient's daily routine and clinical and research practice, considering technical, usability, and ethical aspects.

4.3 Functionalities of the AI-Based APA Tool

The AI-based APA tool will be designed to enhance pain evaluation in oncology by performing three main functions, see Figure 17.

This approach enables patients to track their pain patterns through self-monitoring while providing oncologists with valuable insights into the patient's pain experience, potentially improving pain management and treatment decisions. Additional functionalities identified during the brainstorming session with the research group (see Appendix K) and the interview study (see Chapter 3) were not included in the working concept at this stage but may be considered for future iterations.

The following sections describe and justify the choices made for each functionality.

4.3.1 Data Collection

The first core functionality of the AI-based pain assessment tool is data collection. The tool must gather sufficient and relevant data to enable pain experience monitoring, serve as input for the AI

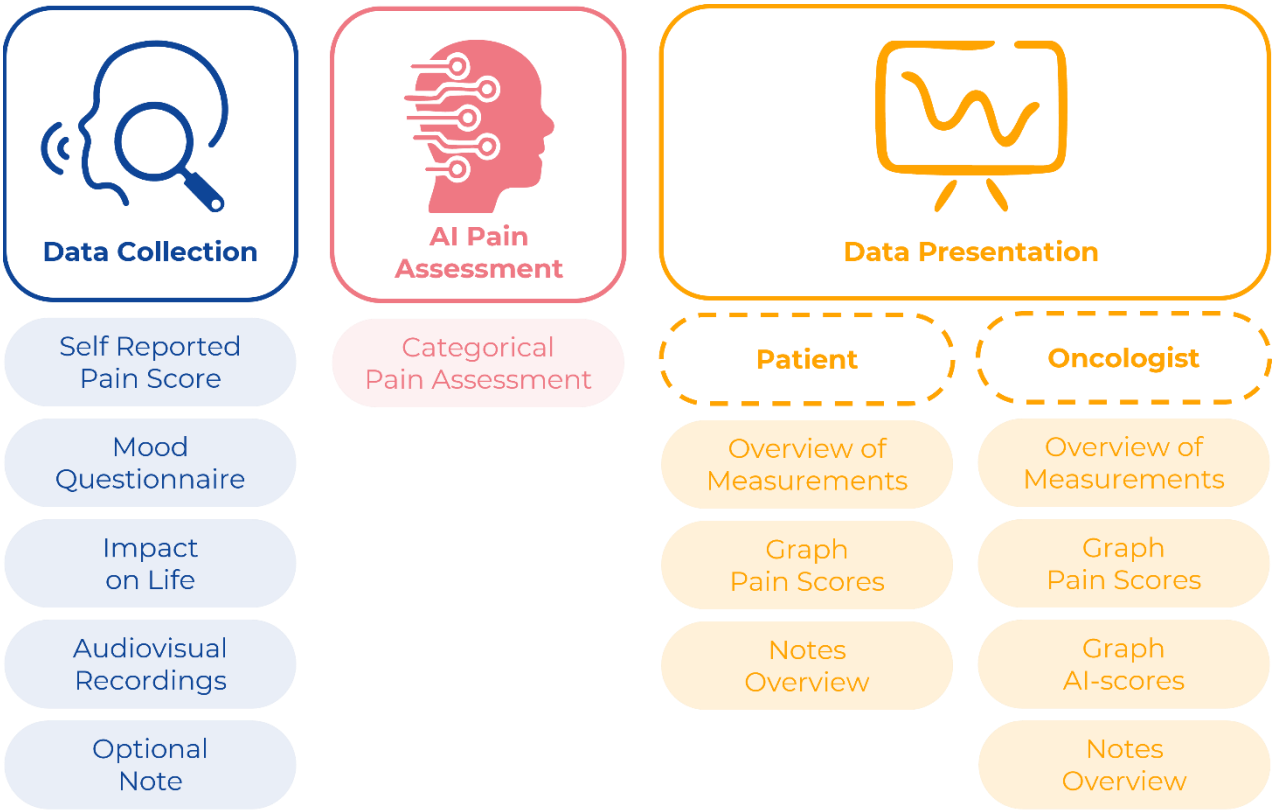

Figure 17 - Overview of the three core functionalities of the tool: 1) Collecting data (blue / left) – Capturing relevant multimodal information for pain experience description and input for the AI-based pain assessment, 2) Analysing data using the AI model (pink / middle) – Processing and interpreting the collected data to predict pain levels, and 3) Presenting data (yellow / right) – Presenting meaningful insights to both patients and oncologists.

model to assess pain accurately, and provide researchers and developers with insights to evaluate and enhance the tool's performance.

Based on the decision to develop an AI model that analyses facial expressions and vocal cues, as well as insights from the literature, the model requires audiovisual recordings of cancer patients experiencing pain, along with a ground truth for training and validation. Additionally, incorporating supplementary contextual information about the patient's pain experience and characteristics may further enhance the model's accuracy and applicability.

4.3.1.1 Population

The AI model is specifically designed to assess pain in cancer patients. This population differs from others, as discussed in the Chapter 2, making it necessary to collect data directly from cancer patients experiencing different levels of pain. The dataset should be representative of diverse patient demographics, including variations in age, gender, and ethnic backgrounds, to ensure broad applicability and fairness in the model's predictions.

4.3.1.2 Audiovisual Recordings

To assess a patient's pain experience, the tool must collect data that contains relevant pain-related information. As outlined in Chapter 2, audio, visual, and physiological signals have been shown to reflect pain-related cues analysable by AI-models. These cues are also found to be used

by human who try to perceive pain in others [193]. Concerning observable actions relevant to pain communication, facial expression is typically the most salient and instructive for the observer [194, 195]. While all three modalities can be captured non-invasively, audio and visual data are more easily obtained and align with the pain anamnesis in current clinical practices. Additionally, the literature review indicates that models trained solely on these inputs achieve strong performances (accuracy: 0.6-0.95). Based on this all together, it was decided that using audiovisual input data would be a suitable starting point for this tool.

To capture facial expressions and vocal characteristics, the tool can either record the audio and visual data simultaneously or separately and the visual data in the format of images or videos. The literature study showed that the temporal dimension of facial expression of pain might provide valuable information on pain dynamics, but the outcomes were not conclusive. To have the opportunity to evaluate the effects of temporal information from facial expressions on the model's performance and to maintain synchronisation between modalities, it was decided that audiovisual recordings were the preferred input.

These audiovisual recordings must capture pain expressions at varying intensity levels to train the model to recognise and interpret pain-related cues effectively. But in addition to pain-related information, it can be hypothesised that the AI model may benefit from data on the patient's neutral expression state. When humans interpret pain expressions, different mechanisms are at play [193]. One of the mechanisms include that we naturally and often unaware compare what a person is displaying to their baseline (neutral) expression to identify deviations that we have learned to indicate discomfort or distress. Similarly, providing the AI model with a reference point for each patient's typical facial and vocal characteristics may improve its ability to detect pain-related changes. The literature study identified the study of Wu et al. [196], which demonstrated that the model's performance improved when a neutral facial state was provided as a reference.

Since capturing the neutral state of both the face and voice was considered feasible and required minimal additional resources, it was decided to include this step in the data collection process.

4.3.1.3 Ground Truth

For an AI-model to learn from the data, two types of approaches could be used: supervised learning and unsupervised learning. In the field of AI-based APA models, supervised learning has been applied much more frequently. As identified in the literature study, different types of ground truth could be used for this supervised learning process: 1) self-report pain-scores, 2) observer-report pain-scores, 3) stimulus levels, and 4) facial action unit codes from the facial action coding system (FACS). Since the aim is to assess naturally occurring pain in cancer patients, using a stimulus-based ground truth was not desired nor practical. While FACS could provide insight into facial muscle movements associated with pain, it does not directly capture the subjective pain experience of the patient. Observer ratings were also deemed suboptimal due to their inherent limitations, as they rely on external interpretation rather than the patient's own perception of pain.

Given these considerations, self-reported pain scores were chosen as the ground truth, as they represent the patient's actual experience and are widely regarded as the gold standard in clinical

practice [197]. Since the model will initially be developed using a supervised learning approach, incorporating self-reported pain scores ensures that the training data aligns with established assessment methods.

4.3.1.4 Context Information

Although audiovisual data and ground truth provide essential inputs for the AI-model, findings from the literature review and exploratory interview study suggest that incorporating additional contextual information could potentially further enhance the AI model's accuracy.

As discussed in Chapter 2 and emphasized by oncologists in the interview study (see Chapter 3), pain is a subjective and multidimensional experience that varies across individuals. Several factors contribute to these differences, including patient characteristics such as age [198], gender [199] and cultural and ethnical background [200]. The effect of these characteristics on facial expression and vocal cues associated with pain are also established [201, 202]. The literature study identified two studies, those of Li et al. [203] and Liu et al. [204], which incorporated age and gender in their models, reporting significantly improved outcomes. Based on these findings, it was expected that age and gender information could enhance the AI model's performance, leading to the decision to collect this data from patients.

Beyond these demographic factors, oncologists in the interview study also highlighted that patients differ in how expressively they display pain, particularly through facial expressions. They raised concerns that such variations could influence the outcomes of an AI-based APA model. Supporting this, the studies of Kunz et al. [190, 205] found that patients can be grouped into distinct 'faces of pain', representing varying levels of facial pain expressiveness. As they concluded distinct expression patterns may inform both human and AI-based pain recognition training. The literature study also identified a relevant approach by Lopez-Martinez et al. [206], who improved their model's accuracy by incorporating a facial expressiveness score, allowing for a more personalised assessment. However, while the level of expressiveness was considered a potentially valuable feature, it was deemed challenging to capture reliably at this stage. One possible method would be to have patients or observers rate expressiveness, but there were concerns about the accuracy of such subjective ratings. As a result, expressiveness scoring was not included in the current implementation but remains a consideration for future improvements.

In addition to patient characteristics, pain type was also identified as a relevant contextual factor. Acute, chronic, and breakthrough pain present differently. Acute pain is typically more visibly expressed, whereas chronic pain often exists in the background and may be less prominently reflected in facial expressions. Patients with chronic pain may also adapt to their pain over time, leading to a reduced outward display of discomfort. Studies indicate that chronic pain is generally less pronounced in facial expressions [207]. Given its potential influence on the AI model's ability to interpret pain cues and the fact that current pain databases mostly contain acute pain data (see Chapter 6), information on chronic pain presence was considered valuable and therefore it was decided to collect this information as well.

Furthermore, oncologists in the interview study stressed the importance of pain context in clinical decision-making, suggesting that this information could also benefit the AI model. They

highlighted several contextual factors, including activity tracking, medication use, sleep quality, pain tolerance and the impact of pain on daily life. Additionally, they emphasized that pain is more than just intensity – other dimensions, such as emotional state, also shape the pain experience. Although adding activity tracking and (rescue) medication tracking was considered, their implementation would shift the app's focus toward general health monitoring, rather than pain assessment. Since multiple existing applications already specialize in these areas, it was decided not to include them. However, prescribed medication data could still be valuable and could more easily be obtained. Even though it may not fully reflect the patient's actual medication usage, it is perceived as a good start.

The suggestion to capture information on the impact of pain on daily life and pain tolerability is driven by the oncologists' need to assess whether an adjustment in pain management is necessary. While a patient may experience pain, it does not always constitute a significant burden or requires medical intervention. The impact of pain on daily life can serve as a measure for pain tolerability, providing valuable insight into whether pain is manageable or interfering with essential activities. Findings from the exploratory study highlighted the challenge of balancing patient preferences with medical decision-making. Oncologists must navigate between respecting a patient's perception of their pain and determining whether treatment adjustments are clinically justified. To support a more actionable approach to pain management, additional information on pain impact and tolerability could enhance decision-making by shifting the focus from pain intensity alone to whether intervention is truly warranted. Since this information can be captured using simple self-reported questions, imposing minimal burden on the patient, it was decided to incorporate assessments of pain impact on daily life and pain tolerability as part of the tool's data collection process. These insights may play an increasingly valuable role in the future development of the tool, helping to refine treatment recommendations and patient-centred pain management strategies.

Additionally, given the significant influence of emotional state on pain perception, the possibility of capturing mood-related information was considered. The exploratory interview study highlighted the challenge oncologists face in integrating all dimensions of pain, as well as the risk that this tool might still not fully capture pain's multidimensional nature. Oncologists emphasized that affective states play a crucial role in pain perception, yet they are often difficult to assess systematically in clinical practice. The literature review confirmed that AI models can incorporate affective state information to enhance pain assessment accuracy [118]. Based on these findings, it was decided to include mood assessment as part of the tool's data collection process. This is expected to provide valuable insights into the emotional component of pain, while also allowing for future evaluation of its contribution to improving AI-based pain assessment outcomes.

Similarly, the research group considered capturing information on the physical dimension of pain, including its location. However, since the exploratory interview study did not strongly highlight the clinical importance of this information and the literature study did not identify its use as input for AI models, it was decided that this would not be a focus at this stage. In a later phase of the project, a dedicated module could potentially be added to explore its relevance and contribution to improving pain assessment.

Figure 18 - Overview of which and how the data elements will be collected by the mobile patient application

Lastly, as highlighted by oncologists in the interview study, allowing patients to provide free-text notes about their pain experience may offer valuable additional insights. By having the option to include personal notes, patients can document aspects of their pain that may not be fully captured through structured assessments. While free-text input may contain a wide range of information, some of which may not be immediately useful for the AI model, offering this option aligns with the principles of user-friendly design. It could also serve as a valuable exploratory tool, potentially revealing new types of information that could enhance pain assessment in future iterations of the model. Therefore, it was decided to include an optional notes section, allowing patients to share any relevant observations or experiences related to their pain.

4.3.1.5 Overview of Data Collection

To conclude the data collection considerations, the AI-based pain assessment tool requires a comprehensive and high-quality dataset to enable accurate and reliable pain analysis. The data collection process must therefore include the elements presented in Figure 18, ensuring that all relevant modalities and contextual information are captured.

4.3.2 AI-Based Pain Assessment

Once the necessary data has been collected, the AI-based APA model must process the input and generate a prediction of the expressed pain level. Different learning tasks can be used for this purpose, as identified in the literature review:

1) Detecting the presence of pain (binary classification: pain vs. no pain).
2) Classifying pain intensity (categorising pain into discrete levels)
3) Estimating pain on a continuous scale (regression-based approach).
4) Determining pain significance (evaluating the clinical relevance of pain for treatment decisions).

While pain detection (task 1) is useful in confirming whether a patient is in pain, its clinical value is limited. Oncologists require a pain intensity assessment, as different levels of pain necessitate different treatment approaches, as outlined in clinical pain management protocols discussed in Chapter 2. Both categorical classification (task 2) and continuous estimation (task 3) could meet this need, but they offer different levels of granularity.

Currently, clinical practice primarily relies on the NRS (11-point scale), but in practical decision-making clinical protocols often group pain into four main categories with advice on the pain management strategy:

- No pain (NRS = 0): No action required.
- Mild pain ($1 \leq$ NRS ≤ 4): No immediate action needed, but proactive monitoring advised.
- Moderate pain ($5 \leq$ NRS ≤ 6): Action needed—first assess the cause, then adjust pain medication if necessary.
- Severe pain (NRS ≥ 7): Immediate action required—first assess the cause, then escalate pain management.

This classification also supports de-escalation strategies, guiding medication tapering when pain levels decrease.

An AI model output aligned with these four categories could potentially offer oncologists clinical value comparable to current pain assessment practices. However, findings from the exploratory interview study indicate that not all oncologists adhere strictly to this categorical framework. Many base their assessment on patients' verbal descriptions or medication use history, rather than precise NRS scores. As such, a four-category output may not be sufficient for every clinician. Some oncologists may benefit from a more nuanced representation of pain intensity, potentially requiring a finer-grained scale or additional contextual information to support their clinical judgment.

When considering increasing granularity, the quality of the ground truth becomes a crucial factor. Although the NRS score is widely regarded as the gold standard, it has inherent limitations that affect what an AI model should aim to achieve. The literature review and oncologist interviews confirm that patients assign NRS scores subjectively, based on personal interpretations of pain intensity rather than a fixed definition. As a result, inter-patient variability is high, making exact NRS predictions inherently unreliable. Rather than attempting to replicate NRS scores exactly, the AI model may be better positioned to provide a consistent and reproducible measure of expressed pain, independent of patient-to-patient variability. This would allow for a more objective and standardised approach to pain assessment, while still aligning with clinical needs.

From a technical perspective, increasing granularity – whether by adding more categories or predicting pain on a continuous scale – introduces greater model complexity. More fine-grained predictions increase the likelihood of classification errors and make model training more challenging, as slight variations in patient expressions could lead to misclassifications. Therefore, a stepwise approach is recommended. Initially, develop a model that classifies pain into four clinically relevant categories. Once a robust foundation is established, explore more granular pain intensity predictions.

When determining the optimal AI output, granularity is not the only consideration. What the model's prediction actually represents is equally important. The fourth learning task identified in the literature – determining pain significance – introduces another perspective: instead of merely classifying or estimating pain intensity, the AI could assess the clinical relevance of the pain in terms of impact on function, tolerability, and treatment necessity. This aligns with oncologists' real-world decision-making, where factors beyond intensity – such as pain acceptability and its impact on daily life – play a role in treatment adjustments, as found in the interview study. If pain

significance were the target, the model might need a different ground truth, such as treatment decisions or patient-reported pain tolerability, rather than just NRS scores.

For now, the NRS-based four-category classification remains the preferred approach, as it aligns with current clinical practices while maintaining technical feasibility. However, future research may explore whether a more detailed pain scale improves clinical usefulness, the feasibility of assessing pain significance rather than just intensity or alternative ground truths that better reflect pain tolerability and functional impact rather than subjective NRS values.

4.3.3 Feedback to the Patient

One of the key functionalities of the AI-based APA tool is providing feedback to the patient. As identified in the exploratory interview study, enhancing patient understanding of their pain experience is a potential benefit of the tool. Feedback can support self-learning, self-management, and improved patient engagement, while also facilitating better communication with healthcare providers.

To achieve this, the tool could provide patients with two types of feedback:

- An overview of their recorded measurements, allowing them to track pain trends over time.
- AI-based pain assessments, though this requires careful consideration regarding its impact on patient perception.

4.3.3.1 Measurements Overview

Based on the data captured by the tool, it can generate a structured summary of recorded pain information, providing patients with insights into their pain trends. While patient interviews are still ongoing, findings from oncologist interviews suggest that patients may benefit from an overview that lists when they have completed pain measurements, a visual trend of reported VAS scores to help identify patterns or fluctuations in their pain experience, and access to personal notes to facilitate more accurate recall of their pain rather than relying solely on memory.

Given these insights, the tool will present a timeline of recorded measurements, allowing patients to track when pain assessments were conducted. Additionally, a visual representation of reported NRS scores will be provided to highlight trends over time, and an option will be available to review personal notes, supporting better pain recall and self-reflection. The list of feedback features will be further refined based on insights gained from ongoing patient interviews, ensuring that the tool effectively meets patient needs.

4.3.3.2 AI Assessments

Another option is to present the AI-based pain assessments. Providing AI assessments could help patients learn from the model's output, potentially improving their awareness of how their pain is expressed and how it fluctuates. However, displaying AI-generated pain levels comes with risks, particularly if the model's assessment differs from the patient's self-perceived pain. This could lead to confusion, frustration, or distrust in the tool. For this reason, it has been decided for now not

to show AI-generated pain assessments directly to the patient. The primary focus will be on self-reported pain scores and pain trends, allowing patients to engage with their own pain data without the potential complications of an AI-predicted score. This decision may be re-evaluated in future iterations, based on patient feedback and further research.

4.3.4 Feedback to the Oncologist

The greatest potential benefit of the AI-based APA tool, as identified in the exploratory interview study, is its ability to provide oncologists with additional information about a patient's pain experience. This information could help identify previously overlooked cases of pain, particularly in the outpatient setting, where pain may not always be actively discussed. Furthermore, by offering insights into pain trends over time, the tool could assist in prioritising pain management during consultations, improving doctor-patient communication, and even overcoming some communication barriers to effective pain assessment.

Yet proven, a major challenge in pain management is the subjectivity and inconsistency of pain assessments. Patients' self-reports can vary based on individual perception, recall biases, or communication styles, and oncologists must balance patient autonomy with their professional responsibility to manage pain effectively. By providing structured and objective feedback, this tool has the potential to improve pain evaluations and inform more consistent and data-driven treatment decisions.

4.3.4.1 Measurements Overview

The tool will present an overview of recorded pain data, including a timeline of completed pain assessments that displays when recordings were made. A visual representation of measured VAS scores over time will illustrate pain trends and fluctuations. Additionally, the tool will provide access to patient notes on pain experiences, offering additional context beyond numerical scores.

4.3.4.2 AI Assessments

For the oncologists, presenting the AI assessments is particularly important, as they provide a more consistently measured and, therefore, sometimes perceived as a more objective representation of pain. As identified in the exploratory interview study, oncologists may view the AI-generated assessments as a new type of clinical measure, like laboratory values that can be referenced during decision-making. To support interpretation, oncologists suggested to include a brief explanation of the AI-generated outcomes, along with contextual information such as population-based reference values. Therefore, it has been decided to present AI-estimated pain levels based on audiovisual data analysis and provide comparisons between AI-predicted pain and self-reported pain scores where applicable. A summary of population-based reference trends will also be included.

4.3.4.3 Notifications

To ensure that oncologists receive relevant pain assessment insights without unnecessary disruptions, the tool will include a notification system that highlights important updates related to

the patient's pain experience. These notifications will serve to improve awareness of pain trends, assist in prioritising pain management, and support timely clinical decision-making.

Rather than requiring oncologists to actively search for updates, notifications will provide targeted prompts when significant pain-related changes occur. This ensures that pain assessments remain actionable and integrated into clinical workflows, without overwhelming oncologists with excessive or redundant information.

The notification system will be designed to align with the tool's overall goal of enhancing pain management by making pain data readily accessible while maintaining efficiency and usability in a clinical setting. Further refinements may be made based on feedback from oncologists as the tool is implemented in practice.

4.4 System Workflow

To effectively implement the functionalities of the AI-based APA tool, a structured approach has been developed to determine how each component will operate. This section outlines the workflows that govern data collection, AI-based pain assessment, and feedback presentation. These workflows have been designed based on technical requirements and feasibility, insights from the exploratory interview study, and key design principles and goals, including usability, reliability, and seamless integration into clinical practice.

Figure 19 shows an overview of the different components of the tool (focussing on the core functionalities) and the dataflow.

4.4.1 Data Collection

To collect the selected types of data, multiple sources could be considered. However, since the goal is to develop a tool that patients can use independently and outside the hospital for daily pain assessment, it was determined that patients themselves should provide the information. This approach ensures that no additional workload is placed on healthcare providers or hospital staff while enabling continuous data collection in real-world settings.

To facilitate this, a device capable of capturing audiovisual data and communicating with a server is required. Given the widespread availability and technical capabilities of modern digital devices, mobile application was chosen as the most practical and accessible solution. Mobile technologies are now widely adopted and well-integrated into healthcare practices, making them a natural fit for this tool.

This decision aligns with the broader mobile health (mHealth) movement, which has become an essential component of medical communication and remote monitoring [208]. mHealth – defined as medical and public health practices supported by mobile devices [209] – has rapidly expanded due to the growing adoption of smartphones [132] and their increasing capacity to support high-quality data collection [210] and real-time health interventions. Studies have demonstrated that mHealth solutions enhance patient engagement, facilitate remote monitoring, and improve data-driven healthcare decision-making [211]. Given these advantages, a mobile application serves as

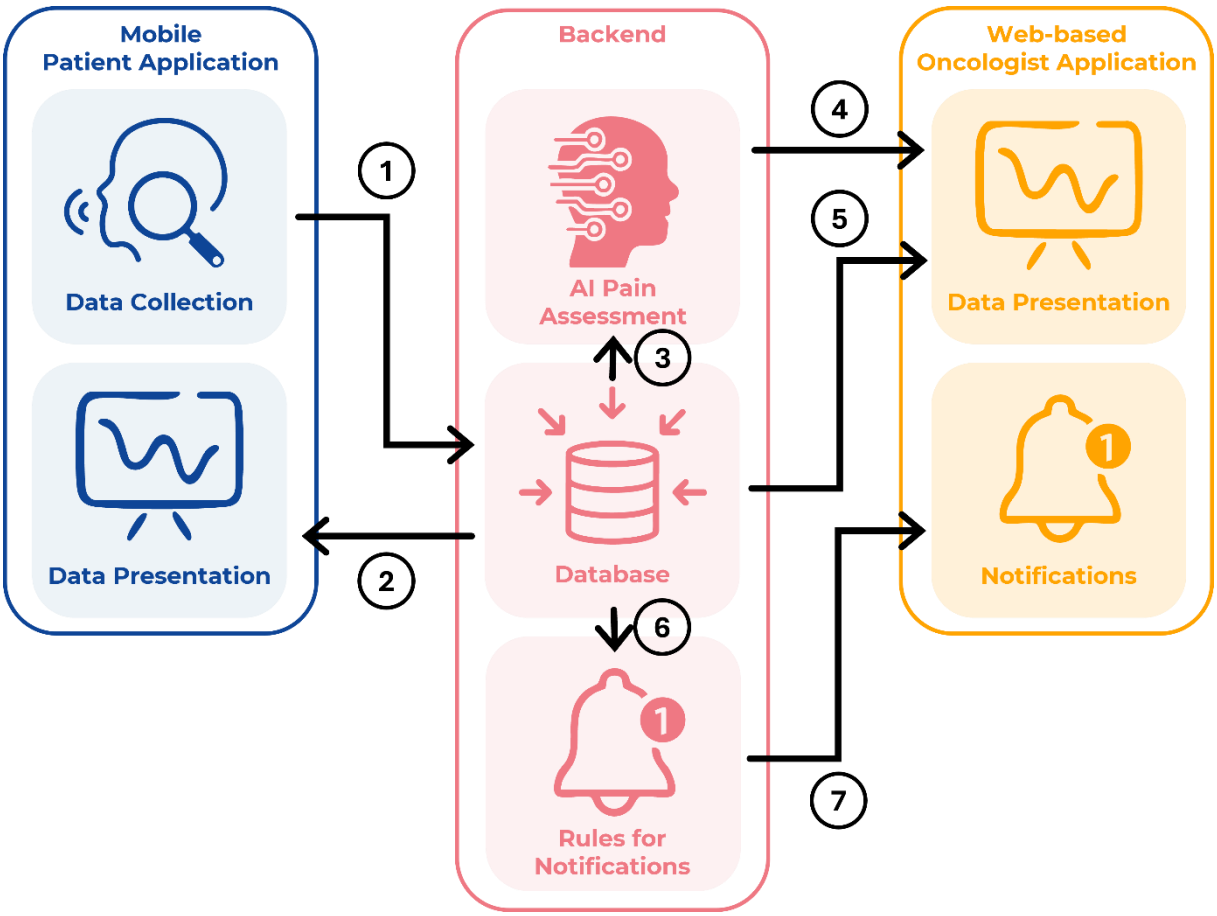

Figure 19 - Systemic architecture of the AI-based pain assessment tool. This schematic illustrates the interaction between the mobile patient application, the backend processing system, and the web-based oncologist application: 1) Patients use the mobile application to record audiovisual data, which is transmitted to the backend and stored in the central database, 2) The raw, unprocessed data (i.e. without AI inference) is also communicated back to the patient app and displayed via the data presentation module, 3) On the backend, the stored audiovisual data serves as input for the AI pain assessment model, which classifies the patient's pain expression, 4) The resulting pain assessment is sent to the web-based oncologist application and displayed in the data presentation module, 5) Additional data entered by the patient—such as VAS scores and textual notes—is also presented to the oncologist, 6) Based on a predefined set of rules, the backend system evaluates whether a notification should be triggered, and 7) If criteria are met, a notification is sent to the oncologist's application to support timely follow-up.

the most effective interface for AI-driven pain assessment, allowing patients to record audiovisual data and receive personalized feedback based on AI model predictions [212].

Instead of developing a new standalone mobile application, the concept could also be integrated into an existing healthcare application. As highlighted in the interviews with oncologists, integrating the tool into established systems offers several advantages. It would allow the use of existing protocols rather than requiring the development of an entirely new platform. Additionally, it would streamline the monitoring process by minimizing the number of new systems that both oncologists and patients need to learn, improving workflow efficiency and adoption. However, since the concept has not yet been validated and its impact on pain management outcomes remains unproven, a standalone application was chosen for the research phase. Developing the tool independently ensures greater flexibility in testing and refinement before considering integration into hospital-specific applications. Furthermore, different hospitals use different digital health platforms, making early integration complex and limiting generalizability. To keep the option open

for future integration into existing applications used by hospitals, such as the DigiZorg application used at EMC, initial contact has already been established. Considerations for future interoperability and seamless integration have been shared, ensuring that the system remains adaptable for potential clinical implementation in later stages of the project.

To ensure that the tool is accessible to as many patients as possible, the application will have to be developed for both Android and iOS platforms. This cross-platform approach allows patients to use the tool on their own smartphones, regardless of operating system, and supports the goal of enabling independent use in diverse outpatient settings.

The next sections explain how the data collection using a mobile application is envisioned to be achieved.

4.4.1.1 Population

The tool is primarily being developed for cancer patients. How patients will access and use the application will depend on the phase of research and its eventual integration into clinical workflows, which will be discussed further in the next two chapters.

For the AI model to be trained and validated effectively within this patient population, certain quality considerations must be considered regarding the composition of the database. A representative dataset is essential to ensure that the model can generalize effectively across diverse patient groups. This requires a balanced distribution of patients across key demographic and clinical variables, including ethnic background, age, gender, and varying levels of pain intensity. A dataset that lacks diversity may introduce biases, potentially limiting the model's ability to provide accurate and equitable pain assessments across different populations. To address this, efforts will be made to collect data from a broad and heterogeneous patient cohort, ensuring that the AI model remains clinically relevant, unbiased, and applicable across diverse demographic groups.

4.4.1.2 Audiovisual Recordings

To capture audiovisual data in which the patients express their experienced pain, a task will have to be set up in the application.

In the first place, audiovisual data of patients who express pain has to be captured. The literature review identified several methods for creating such data: 1) inducing pain stimuli in healthy individuals to elicit controlled pain responses, 2) evoking pain in patients with injuries or conditions through movement tasks that engage affected limbs, 3) recording spontaneous pain expressions from patients experiencing acute pain in emergency or intensive care settings, 4) eliciting pain-related expressions by showing potentially painful scenarios to participants, and 5) capturing pain expression during routine daily assessments, reflecting naturally occurring pain states. Since experimentally inducing pain is invasive and impractical for daily assessments, and acute pain is not consistently present in all cancer patients, a more clinically relevant and feasible approach was chosen: patients will be asked to describe their pain experience over the past day, aligning with standard clinical practices. This method closely resembles the fourth and fifth approaches identified in the literature.

This approach is expected to provide three types of pain-related information:

1. Spontaneous pain expressions – If the patient is experiencing pain at the time of recording, their facial and vocal cues will naturally reflect it.
2. Pain recall expressions – Describing a past pain experience may trigger subtle facial or vocal markers associated with pain memory.
3. Verbal pain descriptions – The spoken content itself provides valuable insights, shown by the fact that this is what is mainly used by oncologists during a pain anamnesis.

The first two types of pain-related information – spontaneous pain expressions and pain recall expressions – will coexist and be utilised by the AI model in this project. However, the third type, verbal pain descriptions, will not be directly incorporated into the current AI model. As a follow-up study or parallel research, this spoken content could be analysed using methods such as large language models to interpret patient narratives in a manner like how physicians assess pain. This could enhance the tool's ability to extract semantic and contextual insights from patient-reported pain descriptions, potentially improving the overall accuracy and depth of pain assessment in future iterations of the model.

Since capturing audiovisual data of a patient in a neutral state was also considered important, a specific task was introduced in which the patient reads a neutral text, or prompt, aloud. This approach is commonly used in mood induction and conditioning trials, where a neutral, non-emotion-inducing prompt serves as a control against emotionally charged responses in experimental conditions [213]. However, introducing a reading task adds extra time to the assessment process and introduces an additional layer of complexity for patients. This could potentially exclude individuals with lower literacy levels from using the application. To ensure the task remains accessible and easy to complete, it was decided that the reading passage should be short, lasting no longer than 10 seconds, and written at a grade 3 reading level. This adaptation ensures that a broader patient population can participate while still maintaining the integrity of the neutral-state recording. At a later stage, if the added value of capturing a neutral state proves to be absent or minimal, this task may be reconsidered or removed to further streamline the data collection process.

4.4.1.3 Ground truth

To collect a self-reported pain score, varies ways exist. The NRS and VAS were the most frequently used measures in literature, see the literature study. Looking at clinical practice, the patient should be asked to report their pain using the NRS-score as part of standard clinical protocol. Although seen in the exploratory study this isn't always the case, the patient will be familiar with the method. Since this method could also be easily captured in a mobile application, it was chosen to use the VAS-score, the visual representation of the NRS-score, as ground truth.

4.4.1.4 Context information

To collect patient demographic information, the application will require patients to complete a simple form providing their age and sex. While ethnic background could also be collected through self-report, this was considered a more sensitive topic. Therefore, during the database

development phase, it was decided that this information would initially be retrieved by the researcher from the EMR, where it is already documented. This allows for accurate and standardized data collection without placing an additional burden on the patient. However, if accessing this information through the EMR proves challenging, an optional feature will be included in the application, allowing patients to voluntarily provide their ethnic background. This approach ensures flexibility while respecting patient comfort and data sensitivity.

The same approach has been chosen for medication information. The researcher will retrieve data on prescribed medications from the EMR, ensuring accuracy and consistency in data collection. However, if accessing this information places too great a burden on the researcher or if it proves to be uninformative for the model, this step will be omitted.

All other contextual information will be collected during the measurement tasks, as it is directly related to the specific moment of assessment. This ensures that the data accurately reflects the patient's current state and experience at the time of recording. To obtain the information on the type of pain (acute or chronic), patients will be asked a simple screening question: "Do you have pain related to your cancer that has lasted for more than three months?". To assess pain interference with daily life and tolerance of the pain, patients will be asked: "Is your experienced pain interfering with your daily activities?" and "Is the pain tolerable at this moment?".

To capture the emotional context, it was chosen to ask the patient to fill out a mood questionnaire. One of the most widely used and validated tools for measuring positive and negative affect is the Positive and Negative Affect Scale – Short Form (PANAS-SF) [214]. However, the original 20-item questionnaire was deemed too time-consuming for patients to complete during routine pain assessments. To enhance the feasibility of frequent measurements while still capturing the emotional dimension of pain, the i-PANAS-SF, a 10-item shortened version, was selected.

4.4.1.5 Measurement Protocol Considerations

The exact protocol for when patients will be asked to perform measurements has not yet been finalized. Insights from the exploratory interview study with oncologists highlighted several challenges that need to be carefully considered in designing an effective and clinically meaningful measurement schedule.

One primary concern is the risk of introducing bias depending on how and when patients are prompted to use the application. If patients are asked to record their pain only when they experience pain, the dataset may overrepresent pain episodes, failing to capture fluctuations in pain intensity or the presence of pain-free moments. Conversely, if patients are instructed to complete assessments at fixed time points, there is a risk that pain may not be present at the time of measurement, limiting the ability to collect data on pain-related expressions and experiences.

Beyond data quality and representation, practical considerations regarding patient burden and engagement must also be addressed. Patients experiencing a pain crisis may find it difficult to complete the assessment tasks, raising concerns about feasibility and compliance. Additionally, the

frequency of measurements must be carefully balanced to capture sufficient data without placing excessive demands on the patient, which could lead to dropout or disengagement over time.

These considerations require further deliberation and refinement in the next phase of the project. The final protocol will need to strike a balance between minimizing bias, ensuring feasibility for patients, and maintaining engagement over time, while still collecting the necessary data to develop a robust AI-based pain assessment model.

4.4.1.6 Quality Considerations

Ensuring the quality of the collected data is crucial for the AI model's performance and reliability, as concluded from the literature study. A high-quality database must be both representative and technically robust, allowing the model to learn from diverse and high-resolution inputs. This resulted in quality considerations to keep in mind for the application.

Providing a mobile application that patients can use on their own devices introduces limitations on the technological requirements that can be enforced. To ensure that a broad patient population can participate in clinical studies using the application, the app must remain accessible and compatible with a wide range of devices. However, for the purpose of developing a high-quality database, certain technical measures may be considered to ensure data reliability and model accuracy. One key consideration is camera resolution, which must be sufficiently high to capture subtle facial micro-expressions that play a crucial role in distinguishing genuine pain from exaggerated or manipulated expressions [215]. Oncologists expressed concerns about potential misuse of the technology, particularly the possibility that patients may attempt to manipulate the system to influence pain management decisions. Developing an AI model that is robust against such manipulations is essential to build trust among healthcare professionals and ensure that the tool provides reliable clinical support. Similarly, audio recordings must be of sufficient quality to detect low-volume vocal changes, such as tremors, hesitations, or tonal shifts, which can be important indicators of pain. Additionally, synchronisation between audio and video is necessary for the AI model to accurately analyse temporal correlations between facial expressions and vocal cues. To address this, collaboration has been established with a specialised department at TU Delft that focuses on data synchronisation. Their expertise will be leveraged to ensure precise alignment of audiovisual modalities, improving the model's ability to analyse pain expressions effectively. Since these technical requirements cannot be strictly enforced for patients using their own devices, additional research could explore the effect of varying technical quality on model performance. Understanding how differences in camera resolution, microphone sensitivity, and synchronisation accuracy impact AI-based pain assessment will be critical in determining how device variability affects real-world applicability.

Lastly, to ensure data consistency, recording conditions should be optimised by minimising facial occlusions (e.g., hair covering the face, glasses reflecting light) and avoiding poor lighting conditions, which could obscure facial expressions or introduce artefacts that interfere with AI processing. A controlled and standardised data collection environment would allow the model to focus on relevant pain-related cues, improving its ability to generate accurate and clinically meaningful pain assessments. However, achieving optimal recording conditions becomes more

challenging when data is collected by patients themselves in non-controlled environments. While some variability is inevitable, efforts should be made to emphasise the importance of high-quality recordings. Patients could, for instance, be instructed to complete the submission alone, in a quiet, well-lit room, preferably against a uniform background to reduce distractions. At the same time, real-world data collection inherently involves uncontrolled conditions, and the model must be designed to be robust to these variations. Instead of relying solely on ideal recording conditions, the AI should be developed to handle inconsistencies and still provide reliable pain assessments across diverse settings. Several studies addressing this challenge have been identified in the literature review [216–218] and could serve as a foundation for developing strategies to enhance the model's robustness to variations in real-world data collection.

4.4.1.7 UX and UI Considerations

The interview study with oncologists highlighted the importance of designing the AI-based APA tool to be accessible and user-friendly for a diverse patient population. Since digital literacy levels vary, the user experience (UX) and user interface (UI) design must ensure that the tool is intuitive and requires minimal effort from patients, particularly those who may already be experiencing discomfort.

To ensure broad accessibility, the application must support multiple languages, allowing patients from different linguistic backgrounds to use the tool comfortably. The interface should be simple and clear, with step-by-step guidance to help users navigate the measurement tasks with ease.

Beyond accessibility, oncologists also raised concerns about patient burden. The tool should be lightweight and efficient, avoiding excessive input requirements that could make it difficult for patients to complete assessments, especially during moments of severe pain. Minimizing the number of interactions while still capturing the necessary data is crucial to maintaining a balance between usability and data completeness.

Another key consideration is patient engagement. Since regular measurements are needed for the tool to be effective, it should be considered to provide non-intrusive reminders to encourage adherence. Patients should have some level of control over notifications and interaction preferences, ensuring that they remain engaged without feeling overwhelmed.

As patient interviews are still ongoing, further UX/UI refinements may be identified based on direct patient feedback. These considerations will guide future iterations of the design to ensure that the tool is inclusive, effective, and easy to use for all patients.

4.4.1.8 Ethical Considerations

As found in both the interview study as well as the literature study, the collection of audiovisual and contextual data for AI-based pain assessment raises several ethical considerations that must be carefully addressed to ensure patient privacy, informed consent, and responsible data handling.

A primary concern is patient autonomy and informed consent. Patients must fully understand what data is being collected, how it will be used, and the potential implications of their participation. Clear and transparent informed consent procedures must be in place to ensure that patients can make a well-informed decision about their involvement.

Data privacy and security are also critical. Given that the tool collects sensitive audiovisual data, strict data protection measures must be implemented to prevent unauthorised access, misuse, or breaches. This includes secure data storage, encryption, and controlled access policies in compliance with ethical guidelines and legal frameworks, such as GDPR or other applicable regulations. How this will be achieved, will be discussed in the next two chapters.

Additionally, the use of AI in pain assessment must not lead to over-reliance on automated predictions at the expense of clinical judgment. The tool should be developed and positioned as a support system rather than a replacement for human assessment, ensuring that oncologists maintain their professional autonomy in making patient care decisions.

4.4.2 AI-Based Pain Assessment

The AI-based APA model will be designed to process audiovisual data collected from cancer patients and generate a pain prediction based on this. This section outlines the concept proposed for the APA model, including the chosen learning task, data pre-processing strategies, model architecture, feature extraction, classification method, fusion approach, and the use of contextual information. The training and evaluation strategies are also discussed to ensure the development of robust model.

4.4.2.1 Learning Task

The learning task of the AI-based APA model is designed to align with the preferred model outcome, as outlined in the previous section. Given the clinical necessity of assessing pain intensity rather than simply detecting its presence, the model will be developed as a multi-class classification system, categorising pain into four clinically relevant levels: no pain, mild pain, moderate pain, and severe pain.

4.4.2.2 Pre-Processing

Data pre-processing is essential for improving model performance by enhancing input quality and reducing noise. Based on findings from the literature review and the expected quality of data, the following pre-processing techniques will be evaluated and applied if useful:

- Facial Data Pre-Processing:
    - Face detection and alignment to ensure standardised input.
    - Cropping and resizing of facial regions to maintain consistency across recordings.
    - Data augmentation techniques (such as flipping, rotation, and brightness adjustments) to improve model robustness to variations in lighting, angles, and occlusions.
- Audio Data Pre-Processing:
    - Segmentation of speech-based audio recordings to isolate relevant speech features.
    - Noise reduction techniques to remove background interference.
    - Standardisation of audio amplitude and pitch variations.

These pre-processing strategies will ensure that the data used for model training and inference is of high quality and representative of real-world conditions.

4.4.2.3 Model Architecture

The model architecture for the AI-based APA tool will be developed through a phased approach, ensuring feasibility while allowing for iterative improvements based on data availability and model performance. The choices made in designing the model are informed by findings from the literature review, prioritising interpretability, technical feasibility, and computational efficiency.

Machine Learning vs. Deep Learning

A fundamental decision in model development is whether to use traditional machine learning or deep learning techniques. Given the current scarcity of high-quality training data, a traditional machine learning approach will be pursued first, as these models require less data to achieve reasonable performance. Deep learning methods typically require significantly larger datasets to avoid overfitting and generalisation issues. Since the development of a representative dataset will take time, starting with a traditional approach allows for a functional proof-of-concept model while the database is being expanded. Once more data is available, deep-learning-based approaches will be explored, and a comparison between the two methodologies will be conducted. This comparison will provide insights into the trade-offs between data efficiency, interpretability, and performance in clinical pain assessment applications.

One-Step vs. Two-Step Approach

For traditional machine learning models, a two-step approach will be adopted, where an intermediate representation of facial expressions is first extracted before classifying pain levels. This decision is based on findings from the literature review, which indicate that two-step models offer better interpretability and explainability, making them more suitable for clinical applications. Unlike one-step models, which learn pain classifications directly from raw data, the two-step approach enables oncologists to understand how the model arrives at its conclusions, fostering trust in AI-assisted pain assessment.

Feature Extraction

Feature extraction plays a crucial role in the performance and interpretability of traditional machine learning models. The literature review identified OpenFace [219] and OpenSmile [220] as widely used and validated toolkits for extracting facial and vocal features, respectively. Given their proven effectiveness in previous APA studies, and the fact that they provide access to features identified as relevant in the literature study, these toolkits will be used for the initial proof-of-concept model. This decision ensures that the development process remains manageable while leveraging established methodologies. At a later stage, custom feature engineering techniques may be explored to enhance model performance.

Choice of Classification Model

Since the learning task involves classifying pain expressions into discrete categories, a classification model must be used. For the initial proof-of-concept, support vector machines (SVMs) and

random forests will be tested. These models were selected because they have been successfully applied in previous APA research, offering robust performance, interpretability, and computational efficiency. SVMs are particularly useful for handling high-dimensional data, while random forests provide an ensemble learning approach that can reduce overfitting. Once the traditional models are validated, deep learning methods – such as convolutional neural networks and recurrent neural networks – will be explored, allowing for a comparison of their advantages and limitations.

Fusion Method for Multimodal Input

Since the APA model integrates both facial expression and vocal cues, the fusion of these modalities requires careful consideration. The literature review identified two primary fusion approaches: 1) feature-level fusion, where extracted features from both modalities are combined before classification, and 2) decision-level fusion, where separate models for facial and vocal data generate independent predictions, which are then combined at a later stage.

The literature did not provide a definitive recommendation on which fusion method is superior. However, for the proof-of-concept model, decision-level fusion will be used first, as it is computationally more efficient and allows for independent evaluation of each modality's contribution. Given that cross-modal relationships may provide valuable insights, feature-level fusion will also be explored in later iterations to assess its impact on model performance.

Incorporation of Context Information

As discussed earlier, contextual factors – such as demographic characteristics and neutral states – could enhance model accuracy by accounting for individual differences in pain expression. However, to avoid overcomplicating the proof-of-concept model, contextual information will not be included in the initial version. Once the model is validated, further research will assess the impact of incorporating contextual data to determine whether it improves performance and clinical applicability.

4.4.2.4 Training and Evaluation

To ensure clinical applicability, the model will be trained and evaluated using rigorous validation methods. The literature study identified four primary validation approaches: 1) leave-one-subject-out (LOSO), 2) k-fold cross-validation, 3) hold-out validation, and 4) external validation. More than half of the reviewed studies applied the LOSO method, indicating its widespread acceptance as an objective validation technique that enhances model generalisability compared to k-fold and hold-out methods. However, despite its advantages, LOSO may not be optimal due to the computational demands and extended training time required, particularly for large models.

For practical implementation, it is also crucial to consider the risk of highly correlated frames from the same subject appearing in both the training and evaluation sets, which can artificially inflate performance metrics. External validation offers the most robust assessment of model generalisability, as it tests performance on an entirely independent dataset. To explore this approach, discussions are ongoing with the Intelligent Sight and Sound research team, who are developing a similar database [221]. Potential collaboration opportunities are being investigated to

determine whether their dataset could be used for external validation, ensuring a more reliable assessment of the model's clinical applicability.

In addition to rigorous validation, interpretability is an important consideration for clinical adoption. AI models must be transparent and understandable to healthcare professionals to support informed decision-making. The literature review highlighted various efforts to improve explainability, including studies such as Liu et al. [204], which employed visualisation techniques to illustrate the contribution of facial landmarks to model predictions. While alternative explanation methods have also been explored, further research is needed to enhance interpretability specifically for clinical applications. At this stage, no specific interpretability approach has been selected for investigation. Given that the current focus is on developing a proof-of-concept, prioritising interpretability may introduce unnecessary complexity. Additionally, during interviews with oncologists, model explainability was not explicitly mentioned as a critical requirement for initial implementation. However, while not an immediate priority, explainability remains an important aspect of AI-based pain assessment and will be explored in future research phases to ensure that the model's outputs are both clinically meaningful and accessible to end-users.

4.4.2.5 Development Approach

The development of the AI-based APA model will be implemented using Python due to its strong support for machine learning and data processing. For facial expression analysis, OpenFace will be used to extract facial action units, while OpenCV and Dlib will assist in video preprocessing and facial landmark detection. For audio analysis, OpenSmile will be applied to extract paralinguistic features relevant to pain-related vocal characteristics. Machine learning models will initially be developed using Scikit-learn for initial experiments with traditional methods, and TensorFlow/Keras for deep learning approaches when sufficient data becomes available.

The development will take place in a structured programming environment, using Visual Studio Code or PyCharm, with Jupyter Notebook facilitating rapid prototyping. Version control will be managed through Git to ensure reproducibility and collaborative development.

4.4.3 Feedback to the Patient

4.4.3.1 Measurements Overview

Patients will have access to an overview of their recorded pain measurements, which will include a list of completed assessments along with their corresponding timestamps. The tool will also feature a detailed graphical representation of reported NRS scores, visually displaying pain trends over time.

To allow for deeper insights, patients will have the option to tap on specific data points for additional details. However, it remains undecided whether the application should provide a written summary of the measurements or include interpretative guidance to help patients understand their pain patterns. These aspects will be further explored in upcoming patient interviews to align the tool's feedback with user preferences and needs.

4.4.4 Feedback to the Oncologist

As outlined in previous sections, the measurements and AI assessments must be presented to oncologists in a structured and accessible manner. During the interviews with oncologists, they indicated a strong preference for receiving this information directly through the EMR. The EMR already centralizes all patient information and includes similar integrated features, such as quality of life questionnaires.

While EMR integration is likely a requirement for final clinical implementation, it is not considered feasible during the research phase. Integration with complex hospital systems like the EMR is time-intensive and would significantly slow down the development and testing process. Moreover, it is not strictly necessary at this stage. Although using a separate system would create some workflow disruptions, such as requiring oncologists to log into an additional platform, interview findings suggest that oncologists are willing to accept this limitation during the research phase, as they are familiar with such constraints in early-stage digital health studies.

One approach would be to rely entirely on the patient for sharing their results. In this scenario, no dedicated digital environment would be provided for oncologists, and patients would either show their results directly via the mobile application or receive automated guidance advising them to contact the hospital when certain pain thresholds are met. While these options minimize technical development, it places the responsibility on the patient and may still lead to inconsistencies in how and when pain data is communicated to healthcare providers, which is one of the defining problems this project is trying to address in the first place.

Another option would be to allow patients to generate and send structured reports containing their pain assessment data to their treating physician via email. This would provide oncologists with standardized documentation of pain measurements without requiring them to log into an additional platform. However, this method introduces potential security and workflow challenges, as sensitive patient data would be transmitted via email, and the information would not be stored in a structured, interactive format.

A more structured solution would be to develop a web-based application where oncologists could log in and access patient pain data in a clear and organized manner. This approach ensures direct access to standardized pain assessments, allowing oncologists to view trends and AI-generated insights within a dedicated interface. However, developing such an application would be technologically more complex, requiring more development time and financial resources compared to the other options. This additional investment in infrastructure may not be justified during the research phase, where the primary goal is to validate the concept rather than to create a fully integrated clinical system.

While full EMR integration remains the preferred long-term solution, the research phase requires a practical and feasible alternative. Currently, discussions are still ongoing to determine the best approach for presenting the pain assessment data to oncologists. At this stage, a web-based application is considered the most effective solution, as it would provide a structured and interactive way to present the outcomes. This approach is expected to best support the perceived benefits identified by oncologists in the exploratory interview study, including improved access to

pain trends and structured AI-generated insights. Since the web-based application is the preferred direction, the next steps in the conceptualization will be developed from this perspective. However, if it is later determined that this approach is not feasible due to technical, financial, or practical constraints, an alternative plan will be devised to ensure that oncologists can still access and utilize the pain assessment data effectively.

4.4.4.1 Measurements Overview

To present pain measurement data effectively, the web-based application will structure the information in a way that supports oncologist decision-making while maintaining usability. The interface will allow oncologists to navigate through recorded pain assessments efficiently, ensuring that all relevant pain data is accessible without requiring excessive interaction.

The system will provide flexible filtering options, allowing oncologists to view data across different time frames or focus on specific periods of interest. Additionally, oncologists will have the ability to select individual pain assessments to access additional contextual information beyond the standard pain score, ensuring that they can explore trends at varying levels of detail.

4.4.4.2 AI Assessments

To complement self-reported pain scores, the AI-generated assessments will be displayed in a format that allows for quick comparison while ensuring that oncologists can easily access more in-depth explanations if needed. The presentation of AI assessments will align with the structured workflow of the application, ensuring that oncologists can integrate the AI insights into their existing evaluation process without disrupting their workflow.

The interface will provide an overview of AI-estimated pain levels, with the option to access further explanation on how the model arrived at its predictions. To maintain transparency and usability, interactive elements will allow oncologists to compare AI assessments with self-reported scores across different time points, reinforcing trend-based insights rather than static, isolated values.

4.4.4.3 Notifications

To ensure actionable and relevant alerts, the notification system will be customizable, allowing oncologists to adjust the sensitivity and type of notifications they receive based on their workflow preferences. The system will be designed to ensure that notifications are clinically meaningful, alerting oncologists to significant trends or deviations rather than routine updates.

The application will include a structured notification log, where oncologists can review past notifications in case they need to revisit an alert. This will ensure that important insights are not lost, even if they are not addressed immediately upon receipt. Additionally, oncologists will have the option to silence or modify notifications based on their clinical priorities, providing flexibility in how they engage with the system.

These design considerations will be continuously refined based on oncologist feedback, ensuring that the notification system remains efficient, informative, and aligned with clinical decision-making needs.

4.4.4.4 Design Considerations

The design of the web-based application for oncologists must balance usability, efficiency, and clinical relevance to ensure seamless integration into their workflow. Based on the exploratory interview study, several key considerations have been identified to guide the development of the interface.

First, clarity and simplicity are essential. The application should present pain assessment data in a structured and visually intuitive manner, minimizing the time required to interpret results. Graphical representations, trend analysis, and side-by-side comparisons between self-reported and AI-assessed pain levels should be easily accessible, without requiring excessive navigation.

Second, workflow efficiency must be prioritized. The system should allow oncologists to quickly retrieve relevant patient data without unnecessary steps or distractions. Filtering and search functions will enable users to view data over specific time frames or focus on individual cases, ensuring that insights remain actionable.

Third, the interface should be adaptive to accommodate different levels of user interaction. While some oncologists may prefer high-level summaries, others may want to explore detailed AI assessments or access raw data for deeper analysis. The design should allow for scalability so that additional features, such as integration with hospital systems, can be incorporated in the future.

Lastly, the system should be minimally disruptive while ensuring critical information is highlighted. The use of notifications and alerts must be well-calibrated to draw attention to important changes in a patient's pain status, while avoiding excessive interruptions that could lead to alert fatigue.

These considerations will be continuously refined based on oncologist feedback, ensuring that the final design remains clinically relevant, intuitive, and aligned with user needs.

4.4.4.5 Data Security Considerations

Given the sensitive nature of patient data, robust data security measures must be implemented to ensure confidentiality, integrity, and compliance with healthcare privacy regulations.

A secure authentication system will be required to control access, ensuring that only authorized healthcare professionals can view patient data. This will include role-based access controls, preventing unauthorized individuals from retrieving sensitive information. Similar to how EMRs function, oncologists should only have access to data from their own patients, rather than a full dataset of all app users. This restriction will ensure patient privacy and compliance with hospital data governance policies.

To protect stored data, all patient records, AI assessments, and pain measurement data will be encrypted, both at rest and in transit. This prevents unauthorized interception and ensures that information remains secure even if the system is compromised.

4.5 Discussion

This chapter presented the conceptual framework for the AI-based APA tool, outlining its core functionalities – data collection, AI-based pain assessment, and outcome presentation. The concept envisions a mobile application for patients to record audiovisual pain data and receive feedback, paired with a web-based application for oncologists to access structured pain insights. This concept integrates findings from a literature review, expert consultations, and an exploratory interview study with oncologists. Together, these elements form a coherent and clinically relevant response to the identified challenges in cancer pain assessment.

One of the main strengths of the conceptual framework is its interdisciplinary and user-centred development process. Insights from clinical stakeholders, technical experts, and scientific literature were successfully synthesised into a coherent and clinically meaningful design. Practical and technical feasibility were considered early in the process, resulting in a concept that is both ambitious and grounded in realistic design objectives. This is reflected, for example, in the decision to initially focus on cancer pain – a condition often underrepresented in existing datasets and models – thereby addressing a clear gap in current APA research. Similarly, the choice to first develop a standalone mobile and web application, rather than integrate directly into EMRs, enhances development flexibility while preserving long-term implementation potential. Together, these decisions demonstrate a careful balance between innovation and feasibility, positioning the tool for both effective research deployment and future clinical integration.

Nonetheless, several limitations and methodological considerations must be acknowledged. First, while this chapter presents a detailed and well-reasoned concept, the conceptualisation process remains incomplete. Although efforts were made to anticipate clinical needs, technical constraints, and practical feasibility, some crucial perspectives – particularly from software developers and implementation partners – have not yet been fully integrated. Their input will be essential for assessing the technical and financial feasibility of the proposed architecture, determining whether the envisioned features can be realistically implemented, and identifying possible constraints that were not accounted for during conceptual design.

Moreover, specific assumptions have been made regarding the AI model development process that merit critical reflection. Although the architecture is informed by findings from the literature and insights from AI experts, many of the detailed modelling decisions – such as opting for a two-step traditional machine learning pipeline, using OpenFace and OpenSmile for feature extraction, and initially applying decision-level fusion – are shaped by the developer's (MK) limited practical experience. In this case, that experience is primarily drawn from programming projects during the Bachelor's and Master's phases of the Technical Medicine programme. While this offers a meaningful starting point, it cannot substitute for the real-world complexity of building and validating clinically robust AI systems. It is therefore expected that the actual development and evaluation process will surface new technical constraints, data limitations, and trade-offs that may require substantial revisions to the current plan. Flexibility and openness to adjusting the modelling approach and re-scoping functionalities will be critical moving forward.

Additionally, although the conceptual framework outlines a comprehensive and well-integrated set of features, not all of them may be technically or logistically achievable within the current scope of the research project. The development of a clinically usable AI-based APA tool – particularly one that integrates context-aware modelling, cross-modal fusion, and structured feedback interfaces – will require iterative design, testing, and optimisation over an extended period. Given the time constraints and available resources of the current project, it is unlikely that all envisioned elements can be implemented at once. Strategic prioritisation will therefore be crucial: development should begin with a robust proof-of-concept based on a minimal viable feature set. Additional funding and the involvement of a broader multidisciplinary team may be required to support the tool's long-term development and clinical implementation.

Another important limitation concerns the nature of the conceptual design process. In an ideal setting, one would begin with a clearly defined problem, explore a broad range of possible solutions, and then converge on the most promising option through iterative evaluation. In this project, however, the idea of using AI to support pain assessment was adopted from the outset and subsequently explored and substantiated through literature review, expert input, and clinician interviews. While this approach is common in applied research contexts, it limited the exploration of alternative solutions that might also address the identified clinical challenges – potentially in simpler, more cost-effective, or more immediately scalable ways. This is a trade-off that must be acknowledged, particularly when considering long-term implementation and generalisability. Nonetheless, the research phase demonstrated that the proposed solution is regarded by stakeholders as both interesting and potentially valuable. Moreover, the chosen direction aligns with the research team's interests and, crucially, with the available technical and clinical expertise required for development. To ensure the solution remains relevant and adaptable, openness to revisiting the concept in light of future evidence or constraints will be essential as development progresses.

A final consideration concerns the stakeholder involvement during conceptualisation. While oncologists contributed valuable insights through interviews, and external experts were consulted at various points, only the core research team was continuously involved throughout the process. There was no formal feedback loop in which oncologists could iteratively review and respond to the evolving concept. To strengthen clinical alignment, future iterations should incorporate participatory design elements, such as feedback workshops or structured testing rounds, with external clinicians. Additionally, patient perspectives – currently missing from the concept – will need to be integrated following the completion of the ongoing interview study. These perspectives are expected to refine the tool's usability, feedback presentation, and emotional impact.

Taken together, this chapter presents a solid conceptual foundation for the AI-based APA tool. The design is grounded in current clinical challenges and developed with attention to both feasibility and future scalability. While the framework is still evolving, it offers a well-structured and thoughtfully considered direction for developing a clinically valuable, user-informed pain assessment tool. The next phases of research will be essential to validate, refine, and prioritise its components through iterative development, technical testing, and continued stakeholder

engagement. By doing so, the concept can mature into a robust application that meaningfully supports pain communication and management in oncology care.

4.6 Conclusion

This chapter outlined the conceptual design of the AI-based APA tool, which is structured around three core functionalities: data collection, AI-based pain assessment, and outcome presentation. The tool will use audiovisual recordings and self-reported pain scores to assess pain levels in cancer patients, with an AI model classifying pain into four clinically relevant categories: no pain, mild pain, moderate pain and severe pain.

To ensure feasibility, the first version of the model will use a traditional machine learning approach with OpenFace and OpenSmile for feature extraction and decision-level fusion for multimodal processing. A mobile application will enable patients to record their pain experiences, while a web-based platform will provide oncologists with structured pain data and AI-generated insights.

This concept ensures that pain assessments align with clinical workflows while remaining technically viable. Future development will focus on application development, data collection, AI model validation, and usability testing, refining the tool based on patient and oncologist feedback to enhance its accuracy and clinical applicability.

5 Application Development

This chapter presents the design and development of the AI-based pain assessment application. It outlines the goals, the design and development strategy, and the key design decisions, which shaped the functionality, usability, and technical implementation of the application. Additionally, the chapter discusses the iterative development process, incorporating insights from stakeholders to ensure the application meets clinical, research, and user needs.

5.1 Introduction

The integration of digital technologies in healthcare has transformed patient care, with smartphones becoming an essential tool for medical communication and monitoring [208]. Mobile health (mHealth) – medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, etc. [209] – has rapidly expanded in recent years, leveraging the widespread availability [132] and increasing technical capabilities of smartphones [210]. As more patients have access to high-quality mobile devices, these technologies present a valuable opportunity for healthcare interventions that enhance patient engagement and data collection [211].

Given this trend, a mobile application serves as a natural and effective interface for AI-driven pain assessment [212]. It enables patients to record audiovisual data while receiving personalised

feedback based on the model's predictions. However, many existing mHealth interventions are designed based on traditional healthcare system frameworks, which may not fully harness the potential of mobile technology or align with user needs [222]. To address these limitations, a user-centred design approach is required, ensuring that applications are developed in close collaboration with end users to enhance usability, accessibility, and clinical relevance. The user interface (UI) and user experience (UX) play a fundamental role in ensuring the accessibility, ease of use, and trustworthiness of the system.

In the context of AI-based pain assessment, a well-designed patient application must be capable of reliably collecting structured pain data while also providing meaningful feedback on recorded pain experiences, as outlined in Chapter 4. To complement this tool and support oncologists in pain management, a web-based application for oncologists can serve as an interface for reviewing AI-based pain assessments and integrating this information into clinical workflows. However, before AI-based pain assessments can be provided, a robust AI model must first be developed, requiring high-quality data. To this end, a clinical database development study will be conducted (see Chapter 6) to capture pain-related audiovisual data in a controlled clinical environment.

Since the primary function of the patient application is to facilitate structured and standardised data collection, this functionality can also be leveraged in the database development study. Using the same mobile application for data collection during the database development study ensures that the AI model is trained on high-quality, clinically relevant data, while also simulating how patients would interact with the application in real-world settings. This approach improves data consistency, enables early usability testing, and enhances the generalisability of the AI model.

To develop these applications for patients, oncologists, and researchers, a collaboration was established with Innovattic, a company specialising in the design and development of digital health solutions. This partnership ensures that the applications are developed with technical expertise while maintaining a user-centred approach. In this process, I have assumed the role of product owner, guiding the development process and ensuring that the application aligns with clinical, research, and user requirements.

This chapter presents the application design and development strategy for the patient, oncologist, and researcher applications, as well as the outcomes of the first two sprints. It details the iterative development process, including stakeholder input and key design considerations. By establishing a structured and validated approach to data collection and AI integration, this work lays the foundation for future clinical studies and potential implementation of AI-assisted pain assessment.

5.2 Methodology

5.2.1 Design Objectives

The objectives of this phase of the project are threefold and align with the required tools for future clinical studies:

1. Develop a smartphone application (iOS) for researchers to facilitate data collection during the database development study in the hospital, enabling efficient recording, annotation and management of audiovisual pain data.
2. Develop a smartphone application (iOS and Android) for patients participating in a clinical feasibility study, allowing them to record pain experiences while receiving AI-generated feedback on their pain assessment.
3. Develop a web-based application for oncologists to visualise and interpret the AI model's pain assessments for patients enrolled in the clinical feasibility study, integrating key measures and outcomes to support clinical decision-making.

5.2.2 Design Approach

The development of the AI-based pain assessment application was carried out in collaboration with Innovattic (Delft, Netherlands). Innovattic was responsible for the technical implementation, including software development, user interface design, and system integration. To ensure a seamless and consistent user experience across both iOS and Android devices, the mobile application was developed using React Native, a cross-platform framework that allows for efficient development while maintaining high performance and native-like interactions. The web-based application for oncologists was developed separately to ensure optimal integration with clinical workflows.

The development process followed a user-centric design approach, ensuring that the application was accessible, intuitive, and aligned with the needs of patients, oncologists, and researchers. In this process, I assumed the role of product owner, coordinating between the research team and the development team to ensure that the application's requirements were grounded in clinical and

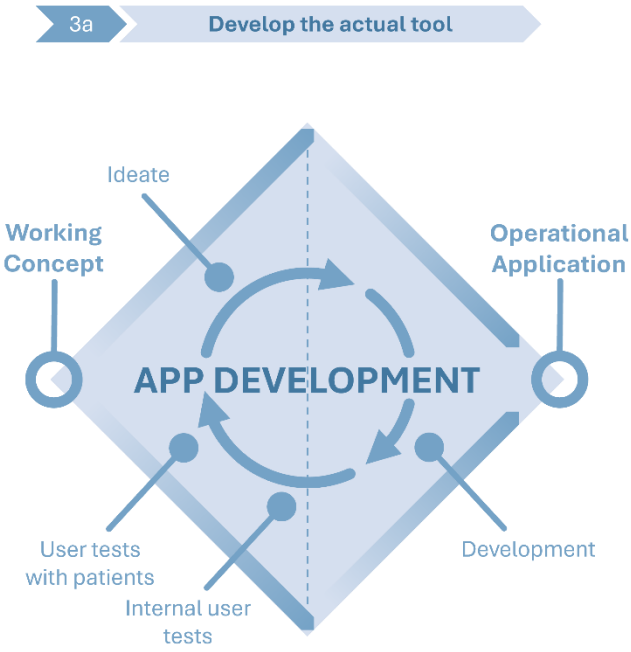

Figure 20 - User-centric App Development Process: from working concept to operational application

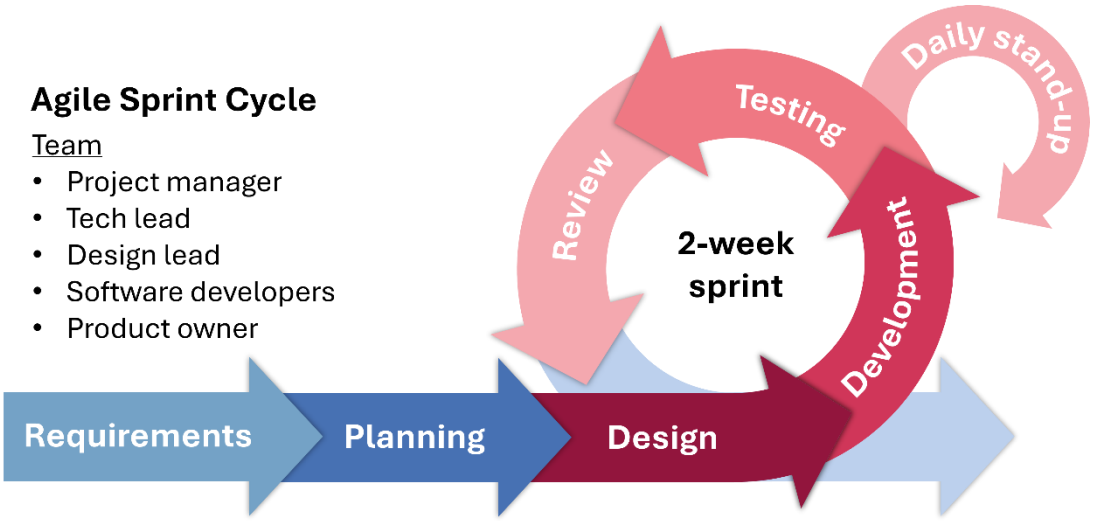

Figure 21 - Agile sprint cycle used during technical development of the application

research needs while being technically feasible. A multidisciplinary team was involved in the development, consisting of a project manager, tech lead, Android / iOS / React Native developers, UX/UI designers, product owner and key stakeholders from the research team. This collaboration ensured that the application was designed with both technical robustness and clinical relevance in mind.

To guide the overall design trajectory, the team adopted a high-level iterative development cycle that moves from a working concept, presented in Chapter 4, to a tested operational application. This cycle is illustrated in Figure 20, which captures the continuous feedback loops between ideation, development, and user testing.

Based on this foundation, an Agile methodology was adopted to implement the technical development process in structured and iterative steps. Five two-week Agile sprint cycles enabled frequent delivery of usable components, integrated feedback loops, and continuous alignment with evolving research needs. The development sprints followed the classic Agile rhythm of planning, design, development, testing, and review, with daily stand-ups, as shown in Figure 21.

5.2.2.1 Agile Sprints

Each sprint followed a set process, beginning with defining its objectives based on project priorities and stakeholder feedback. Requirements derived from the conceptual framework (see Chapter 4) were further refined and prioritised using the MoSCoW method (Must-have, Should-have, Could-have, and Won't-have) to ensure alignment with user needs while maintaining technical feasibility.

Once the sprint objectives were set, UX/UI designers developed wireframes to conceptualise the application layout and functionality. Regular design discussions between UX/UI developers and product owner ensured that usability and functionality aligned with clinical and research requirements. The team created detailed user stories to break down features into actionable development tasks.

During refinement and planning sessions, the team evaluated and prioritised user stories, ensuring a structured and efficient development process. These sessions focused on clarifying feature specifications, determining development priorities based on urgency and impact, and assessing technical feasibility with software developers. Sprint planning meetings finalised the roadmap for each development cycle, allocating tasks and setting clear timelines.

During sprint execution, daily stand-up meetings provided a platform for developers, designers, and product owner to review progress, address challenges, and align on short-term goals. At the end of each sprint cycle, a demonstration session was held to showcase the newly implemented features and collect feedback. The testing was conducted in two phases, beginning with internal testing, where the development team evaluated the system to identify and resolve usability and technical issues. To also assess the application's functionality and accessibility with end-users, user-tests have been scheduled.

Following each sprint, a retrospective session was held to reflect on the sprint's outcomes, evaluating what worked well and identifying areas for improvement. These sessions helped refine the development process by addressing challenges and optimising workflows for subsequent sprints, ensuring continuous improvement and alignment with project goals.

5.2.2.2 User Testing

The user testing phase has been incorporated as an addendum to the exploratory interview study and will be conducted at the Erasmus University Medical Centre (EMC). The structure of the interview remains unchanged; however, between the first and second part, patients will interact with a clickable prototype of the application. This hands-on experience provides a clearer understanding of the tool's concept, enabling more informed discussions during the second part of the interview, where participants will share their attitudes toward the technology.

The usability test sessions are designed to last approximately thirty minutes, focusing on assessing the clarity of the interface, the intuitiveness of interactions, and the overall user experience. Recruitment is currently ongoing and is being facilitated through collaboration with the Nederlandse Federatie van Kankerpatiëntenorganisaties (NFK). To ensure sufficient patient participation, a news announcement was published on the NFK website, and relevant sub-organisations were contacted.

User tests are scheduled for May 2025, with findings expected to inform iterative refinements to the application. The outcomes of these tests will help identify potential usability challenges, enhance the interface design, and optimise the overall user experience before proceeding to further clinical validation. Insights gathered from patient interactions will be directly integrated into the development process, ensuring that the application remains accessible, intuitive, and aligned with patient needs.

5.2.3 Planning

The development of the AI-based pain assessment application is structured into five Agile sprints, each focusing on different aspects of the mobile and web-based applications. While the planning provides a structured roadmap, it remains flexible to accommodate insights gained from user

feedback and iterative development. At present, the first two sprints have been completed, while the remaining sprints are scheduled for the rest of the year.

The first sprint focused on delivering a minimum viable product (MVP) for the research application used in the database development study. This version included the recording module, allowing researchers to collect audiovisual pain data in a structured and controlled manner. This foundational component ensured that high-quality training data could be gathered for the AI model.

The second sprint addressed the development of the patient application, implementing essential features such as authentication, sign-in, and onboarding. These functionalities were crucial to providing a secure and user-friendly experience, enabling patients to access the application and navigate it with ease.

The remaining sprints will take place throughout the year, further refining the application and expanding its functionalities. The third sprint will focus on the home screen, further development of the recording module, and the integration of an outcome presentation module for the patient application. The fourth sprint will shift attention to the web-based application for oncologists, establishing authentication, sign-in, and onboarding processes to ensure a secure and structured user experience for clinicians. Finally, the fifth sprint will focus on the outcome presentation module for the web-based application, ensuring that oncologists can easily interpret and utilise AI-generated pain assessments in their clinical workflow.

5.3 Results

5.3.1 Software Architecture

The software architecture is presented in Figure 22, illustrating the interaction between the patient application, oncologist application, admin panel, backend, AI model, and research database. The patient application, oncologist application, and admin panel interact with the backend through defined application programming interface (API) endpoints to exchange data securely. The AI Module is integrated into the system via an internal API, allowing model predictions and updates to be handled programmatically. Synchronisation with the Research Database is also managed through API-based data flows, ensuring modularity and controlled access.

The AI-based pain assessment tool is being developed and hosted by Innovattic, ensuring a stable and secure infrastructure for both the patient-facing mobile application, the web-based application for oncologists, and an administrative panel. These components communicate with Innovattic's backend, which manages data flow, storage, and interaction with the AI model.

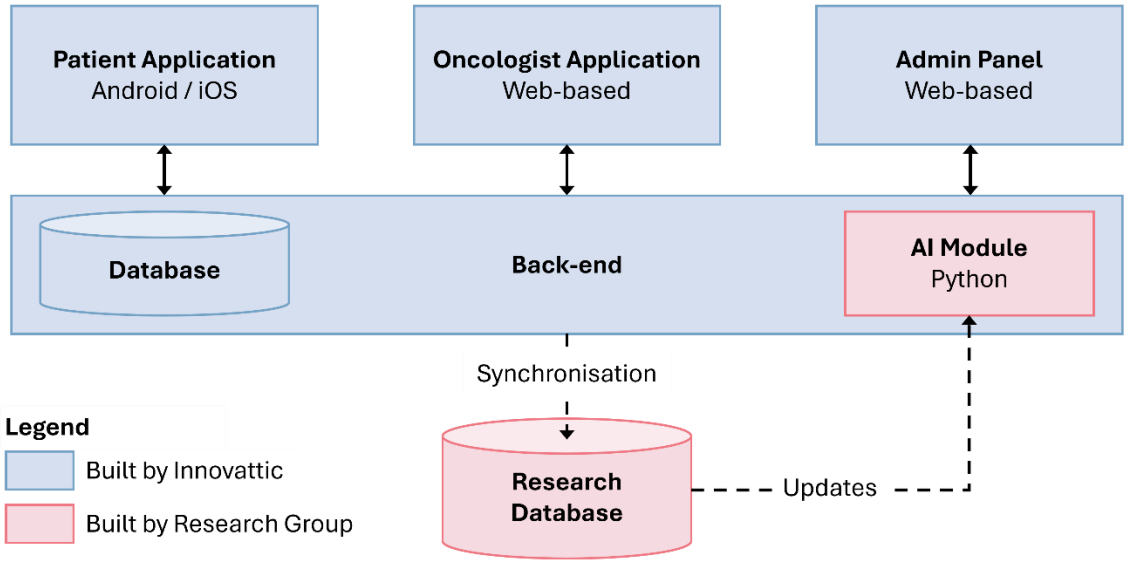

Figure 22 - Software architecture for the SENSAI-project

At the core of the system is a backend server, which includes a database where patient and oncologist interactions with the application are securely stored. While Innovattic is responsible for hosting and maintaining the backend, the AI model itself is developed and managed by the research team. Innovattic's system does not include AI development but instead facilitates communication with the AI model via an application programming interface.

The backend serves as a bridge between the applications and the research database. The patient application, oncologist application, and admin panel interact with the backend to retrieve and update information. In turn, the backend securely transmits relevant data to the research database, which plays a critical role in training and refining AI models. As the research team develops new iterations of the AI model, updates are occasionally sent back to Innovattic's backend, ensuring that the AI module running on the server remains up to date with the latest improvements.

This architecture enables a clear separation of responsibilities: Innovattic manages the application's infrastructure and backend, while the research team retains control over AI development and model training. By establishing a structured API for communication, the system ensures scalability, security, and flexibility, allowing future iterations of the AI model to be seamlessly integrated without disrupting clinical workflows.

5.3.2 5 Sprint 1

5.3.2.1 Requirements

The focus of the first sprint was to deliver the MVP for the application that could be used on a research phone during the database development study. The requirements for this MVP were divided into Must-have, Should-have, Could-have, and Won't-have categories based on their importance for early-stage development and feasibility within the sprint. The MoSCoW overview is presented in Appendix L.

The primary Must-have requirements focused on ensuring the accurate and reliable collection of all necessary data for the database development study, while also implementing secure data storage measures to comply with data protection and privacy regulations. Additionally, the requirements were designed to ensure that the MVP seamlessly integrated into the practical workflow of the database development study.

5.3.2.2 User Flows

The established user flows integrate both researcher and patient interactions and are presented in Figure 23.

The process begins with the researcher entering the participant ID of the patient into the mobile application. This step ensures that the collected data is correctly assigned to the respective participant, maintaining data integrity and traceability. Once the participant ID has been entered, the researcher hands over the mobile device to the patient, allowing them to independently complete their data collection tasks.

The patient is first presented with the VAS-score input screen, where they are asked to rate their current pain intensity. Once this is completed, the application proceeds to the mood questionnaire, where the patient evaluates their affective state using a validated Likert-scale format.

Following the questionnaire, the patient is introduced to the recording tasks. The application provides instructions on how to perform the recordings, including guidance on maintaining proper positioning within the frame. The patient is also given the option to pre-read the recording prompt before starting. The first recording task then begins, in which the patient is given a structured prompt to respond to. After completing the recording, the system asks whether a retake is needed, allowing the patient to repeat the recording if they were disturbed or dissatisfied with their response.

Next, the patient is guided through the narrative recording task, which follows a similar process. The application provides instructions, allows the patient to pre-read the prompt, and then proceeds to the recording session. Once completed, the system again offers the option for a retake if necessary. If the patient chooses not to redo the recording, they are given the opportunity to leave a free-text note, allowing them to provide additional context or comments about their pain experience.

Upon completing all tasks, a final screen notifies the patient that the data collection session is complete and instructs them to return the mobile device to the researcher. The researcher then reviews the collected data through an overview screen, which displays the recordings, VAS score, and mood questionnaire responses. The researcher can play back the video recordings to check for technical issues, such as ensuring that the patient's face is fully visible and correctly positioned in the frame. If a recording does not meet quality requirements, the researcher has the option to redo the recording session. Once all data has been approved, the researcher selects the option to save the data to the mobile device, ensuring that all collected information is securely stored for future analysis.

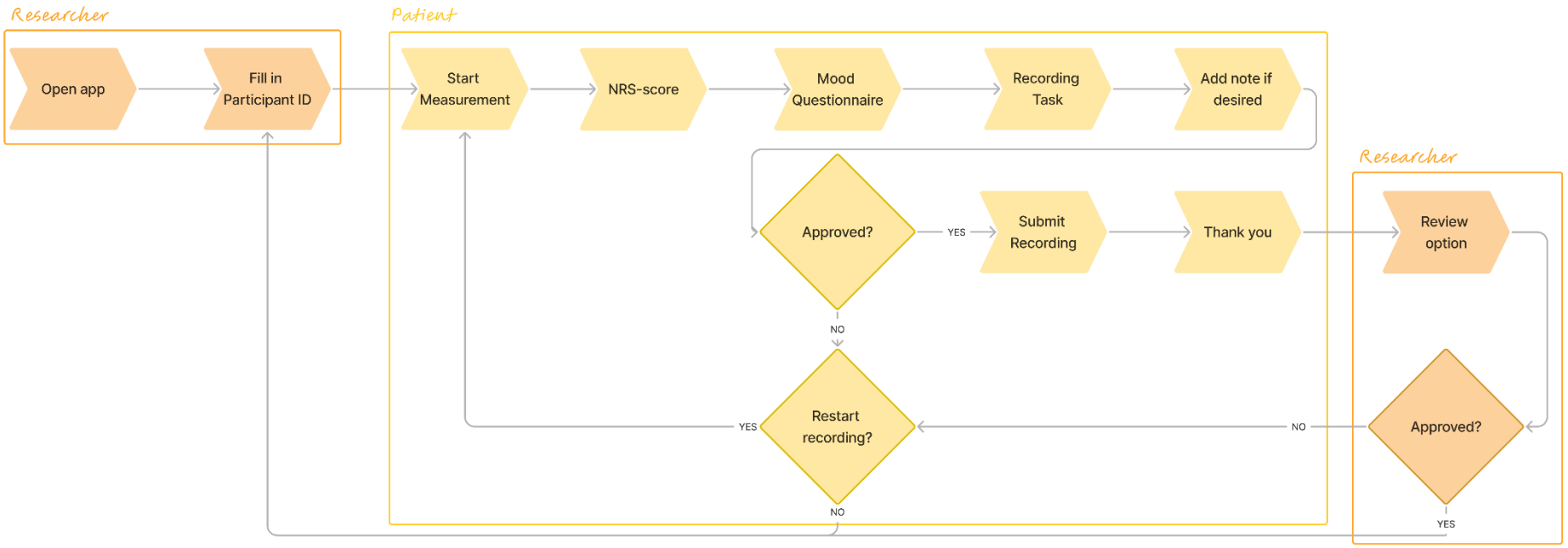

Figure 23 - User Flows for the researcher application, which will be used during the database development study for data collection (see Chapter 6)

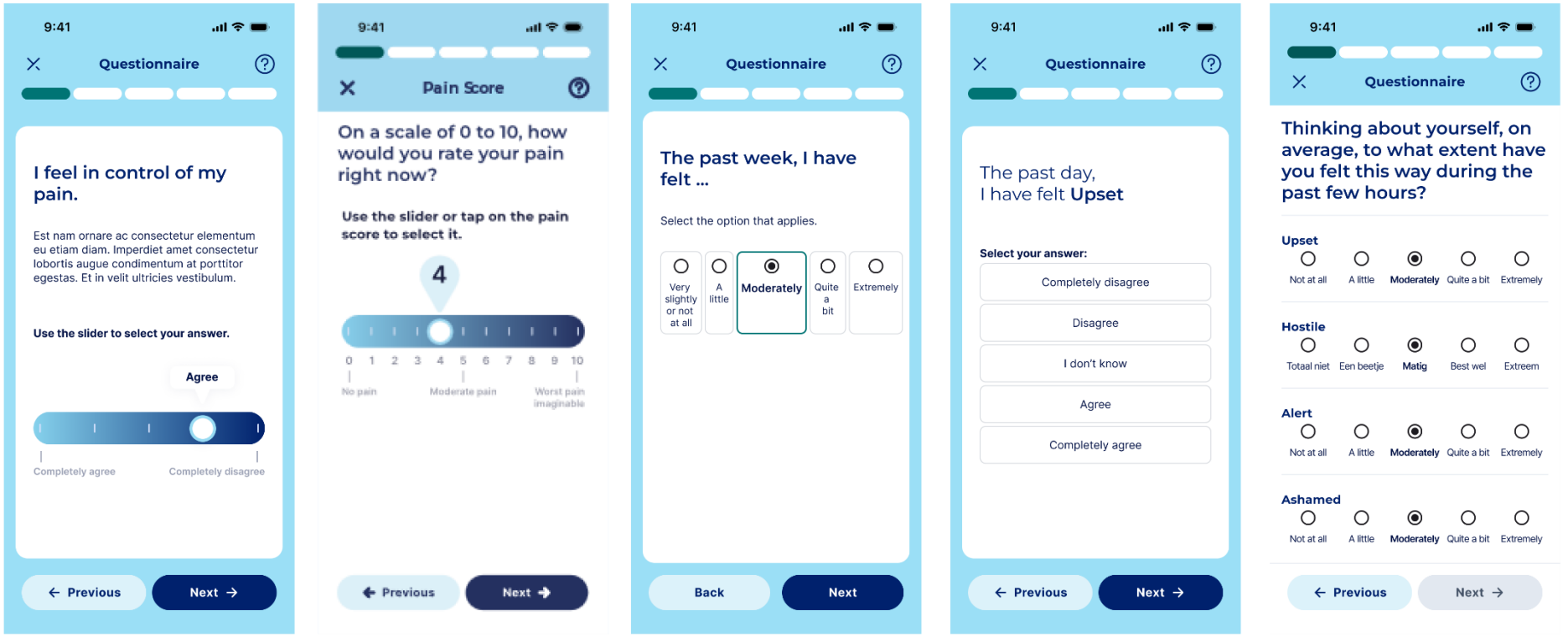

Figure 24 – Examples of some concepts considered for the UX/UI of the data collection module of the researcher application:
a) Two considered slider concepts for the VAS-score reporting (descriptive labels vs numbered labels for selection) (right was finally selected)
b) Three considered questionnaire concepts for the mood questionnaire (i-PANAS-SF) (all radio-buttons but differently arranged) (right was finally selected)

5.3.2.3 UX/UI Design

VAS-score

For the user interface design of the VAS-score, various interaction models were evaluated, including radio buttons, dropdown menus, and discrete sliders. The selection process was guided by existing research on the validity and reliability of response widgets for self-reported pain assessment. Studies have shown that both radio buttons and sliders provide reliable data collection methods for numerical pain scales [223]. Additionally, research comparing endpoint-only labels versus fully defined choice points found no significant difference in user preference or response accuracy [224].

A slider format was ultimately chosen due to its ease of use, intuitive interaction, and consistency with validated pain assessment methods. Studies indicate that sliders can be used without compromising data quality [225], making them a suitable alternative to traditional radio buttons. Furthermore, research comparing different response scales (VAS, Likert-7, and Likert-11) highlights high agreement rates among formats but suggests that multi-point scales (7 or 11 choices) facilitate more precise self-reporting [226].

Some concepts that were considered are shown in Figure 24.

In implementing the slider, a "touch-and-go" interaction model was integrated to allow users to quickly select their pain level without requiring excessive interaction, enhancing usability. A colour gradient was incorporated to visually indicate increasing pain intensity, and descriptive labels ("no pain," "moderate pain," "worst pain imaginable") were included to maintain clarity. These design choices ensure that the interface remains both clinically valid and user-friendly, facilitating accurate pain reporting while minimizing cognitive and interactional burden on patients.

Mood Questionnaire

For the mood questionnaire, the patient is asked to complete the i-PANAS-SF [227] (or Dutch version [228]) questionnaire. The patient will rate the applicability of 10 affective states on a 5-point Likert Scale, from ‘not at all’ till ‘extremely’, as in the validated version. This questionnaire assesses mood by having patients rate the applicability of 10 affective states using a 5-point Likert scale, ranging from "Not at all" to "Extremely", consistent with the validated format.

Regarding the presentation format, both horizontal and vertical orientations were considered, see Figure 24. Research suggests that a horizontal layout is preferable when users are expected to make relative comparisons, as it allows for quicker scanning and more intuitive selection [229]. Conversely, a vertical layout is often recommended for independent questions, as it reduces cognitive load and ensures clear differentiation between items. In addition to readability and cognitive effort, the number of required interactions (e.g., clicks or scroll actions) was considered to minimise patient burden. Although the independent nature of the i-PANAS-SF items would typically suggest a vertical layout, this approach would require patients to scroll frequently or navigate through multiple pages to complete the questionnaire. To optimise usability, it was determined that a horizontal format with radio buttons could accommodate five questionnaire items per screen without requiring additional scrolling or page transitions. This design choice

aimed to balance efficiency and clarity, ensuring that patients could complete the questionnaire with minimal effort while maintaining the validated structure of the i-PANAS-SF.

Recording Tasks

To ensure standardized and high-quality audiovisual data collection, the recording tasks were designed with clear guidance and intuitive visual aids. Patients receive instructions on how to position themselves correctly while filming, ensuring their face remains within the frame.

To facilitate proper alignment, a '+' symbol is displayed on the screen, indicating the correct placement of the nose, while a head-shaped overlay provides a visual cue for maintaining the appropriate distance between the face and the camera. These elements help ensure consistent framing across recordings, which is essential for accurate AI-based pain assessment.

Additionally, recognizing that some users may have difficulty reading or require additional support, an option to pre-read the recording prompt before starting the task was integrated. This feature allows patients to read the instructions at their own speed, reducing cognitive strain and ensuring that all users can fully understand the task requirements before beginning their recording.

5.3.2.4 Delivered Product

After the first sprint, three out of the four components of the patient task were successfully implemented. Figure 25 presents screenshots of the completed sections, which include the VAS-score input, the recording task, and the outcome presentation module. However, due to time

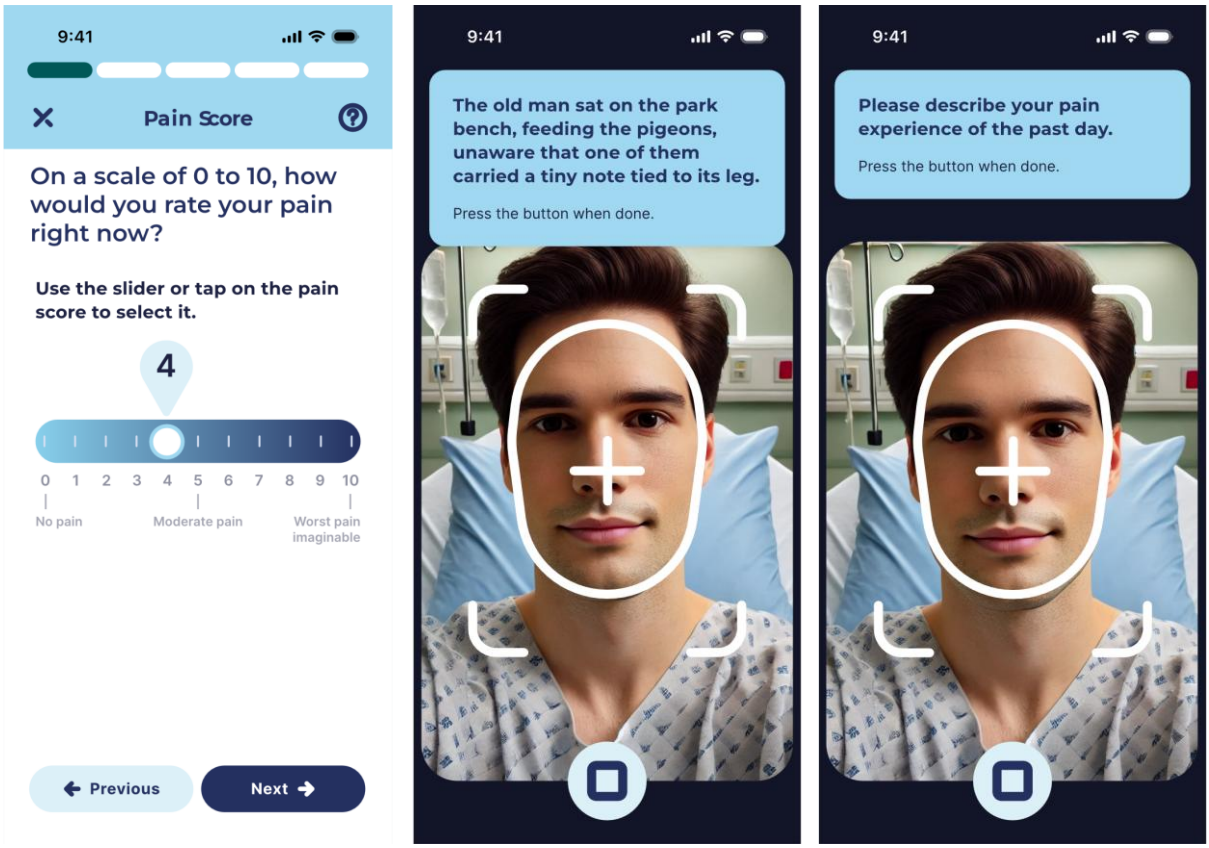

Figure 25 - Screenshots of the delivered product after the first sprint.
Developed in collaboration with Innovattic, Delft, the Netherlands.

constraints, the mood questionnaire component was not delivered within this sprint and was deferred to a later development phase.

The patient input was successfully recorded and, after review, could be saved directly to the researcher's phone. This ensured that data integrity was maintained while allowing researchers to verify recordings before storage. The implemented functionality enabled secure local data management, laying the groundwork for future synchronization with the research database.

5.3.3 Sprint 2

5.3.3.1 Requirements

As in the first sprint, the requirements from the conceptual framework were discussed with the development team, and those specific to the patient application were structured into a MoSCoW-requirements overview, see Appendix L.

Given that the second sprint focused on authentication and onboarding, the requirements were further refined in consultation with privacy officers at EMC to ensure compliance with security and data protection standards.

This process led to the establishment of key Must-have requirements, including two-factor authentication (2FA) and automatic logout after a period of inactivity, both essential for safeguarding patient data. Since a seamless and intuitive first-time login experience was a priority, the onboarding process was also a key area of focus. As a result, an introductory guide was integrated into the application to clearly explain its purpose. In a following sprint a tutorial will be added to this to ensure that patients could navigate the system with ease and confidence.

5.3.3.2 User Flow

The established user flow is presented in Figure 26.

The process begins when the patient receives their participant identification number (ID) and a first-time password from their oncologist on paper. Along with these credentials, they are given instructions on how to install the application. Upon opening the app for the first time, the patient is prompted to enter their participant ID and the provided password. After submitting this information, a one-time authentication code is automatically sent to the email address or phone number on record with the research team. To proceed, the patient must enter this code in the app, completing the 2FA verification step.

Following successful authentication, the onboarding process begins. The patient is introduced to the purpose of the application and guided through its key functionalities. At this stage, they are required to create a 4-digit PIN and confirm it by entering it twice. Once the PIN is set, it becomes the default method for logging into the application, eliminating the need for 2FA during future logins. If the patient's device supports biometric authentication, such as fingerprint or facial recognition, they are given the option to enable it. If activated, biometric login becomes the preferred method for future access.

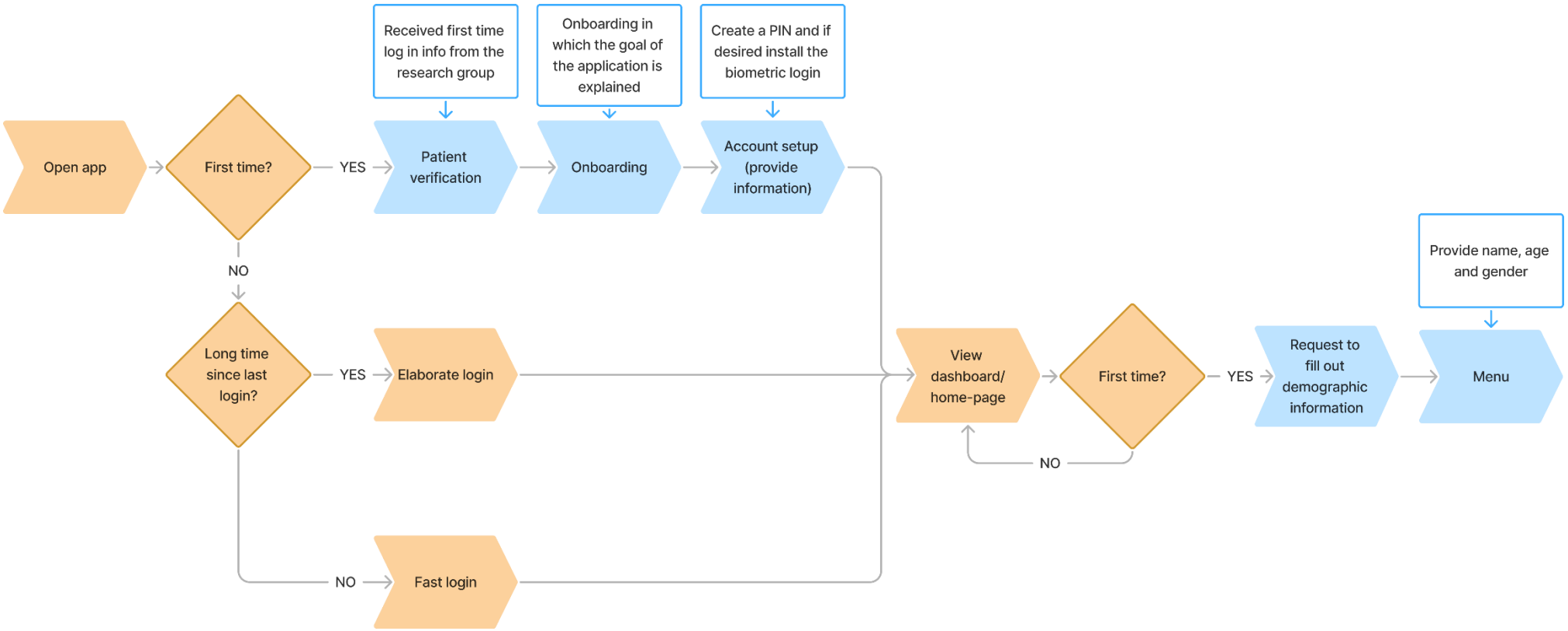

Figure 26 - User flow for authentication, fast sign-in and request to fill out demographic information

After completing the onboarding process, the patient is directed to the home page. Upon their first visit, a request appears asking them to provide basic demographic information, including age and gender. Additionally, they are given the option to enter their name, which the app will use in personalized messages and prompts. Completing this step finalizes the initial setup and allows the patient to begin using the application's features.

For subsequent logins, the patient can use their chosen authentication method, either the PIN code or biometric login. Upon successful authentication, they are taken directly to the home page. From there, they can access the menu, which provides options to adjust personal preferences, view additional information about the SENSAI project and participation in medical research, and retrieve contact details for the research team. If they wish to contact the research team, the app includes a direct contact button that automatically drafts an email addressed to the product owner, pre-filled with their participant ID to facilitate communication.

To enhance security, the system includes a reactivation measure for inactive users. If a patient has not used the application for more than one week, the app will require them to complete the 2FA process again upon their next login. This additional security step ensures that access remains protected while maintaining a balance between convenience and safeguarding patient data.

5.3.3.3 UX/UI Design

The implementation of multiple authentication options (biometric login, PIN-based authentication, and email confirmation) was based on research indicating that multimodal

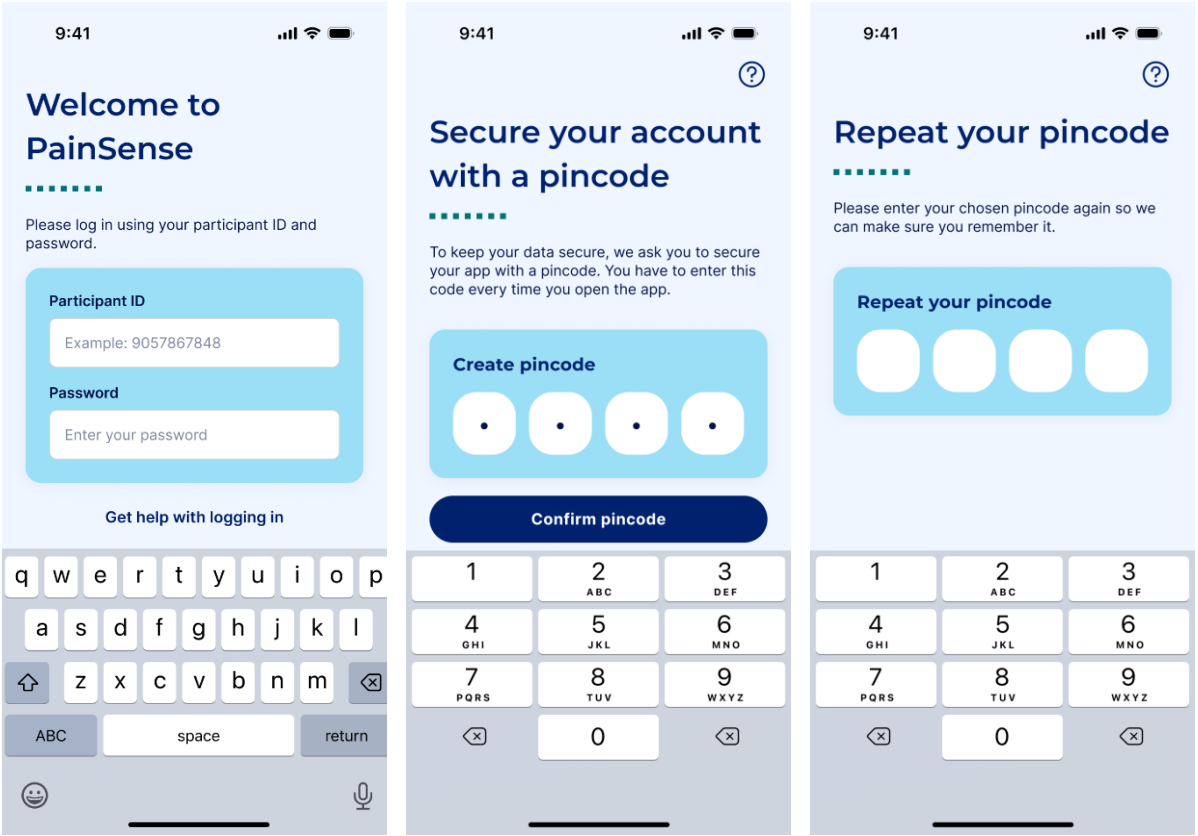

Figure 27 - Screenshots of the delivered product after the second sprint.
Developed in collaboration with Innovattic, Delft, the Netherlands.

authentication methods improve both security and user experience in mobile health applications [230]. Studies suggest that biometric authentication reduces login time and cognitive burden, particularly for older or less tech-savvy users, while PIN codes provide an essential fallback mechanism [231].

The decision to implement an automatic logout function was informed by security guidelines for mobile health applications, which recommend automatic session termination after prolonged inactivity to mitigate unauthorized access risks.

5.3.3.4 Delivered Product

After the second sprint, a part of the authentication and log-in procedure was delivered, see Figure 27 for screenshots. While the front-end components of these features have been implemented, internal testing is still ongoing to assess usability and performance. The backend functionality is not yet fully operational.

5.4 Discussion

This chapter presented the design and development process of the AI-based pain assessment applications for patients, oncologists, and researchers, as well as the outcomes of the first two development sprints. The first sprint resulted in an initial prototype of the researcher application, enabling structured audiovisual data collection for the database development study. However, due to time constraints, the mood questionnaire component was not completed within the sprint and was deferred to a later phase. Despite this, the data collection workflow was validated, allowing researchers to efficiently review and store collected data. The second sprint focused on the authentication and onboarding process for the patient application. 2FA, PIN-based login, and optional biometric authentication were introduced to enhance security while maintaining usability. A structured onboarding process was designed to familiarise patients with the application's functionalities and collect demographic information. While the front-end components were successfully implemented, backend authentication functionalities remain under development and require further testing before full integration.

Although the development process is still in its early stages, an important challenge has already emerged. Despite careful planning and structuring of sprints, not all user stories were fully delivered as expected. This highlights the need for continuous evaluation and refinement to optimise the Agile development approach, ensuring that the application aligns with the three folded design objectives.

The development process remains ongoing, with future sprints focusing on completing key components. The next phases will involve the design and implementation of the mood questionnaire, the development of the measurement presentation module for patients, and the creation of the web-based application for oncologists. Additionally, the backend infrastructure needs to be finalised to ensure secure data management and enable seamless communication with the AI module.

Usability testing with patients has been initiated but still needs to be conducted. These tests will provide valuable input for iterative refinements, ensuring that the design and functionality of the applications align with user needs. The findings will directly inform further design adjustments, contributing to the usability, accessibility, and clinical relevance of the system.

These next steps are essential to progress towards its usage in clinical research, ensuring that the application functions effectively in real-world settings. Ultimately, this development aims to lay the foundation for the integration of AI-assisted pain assessment into oncology care, enhancing both patient self-reporting and clinical decision-making.

5.5 Conclusion

This chapter presented the iterative development process of the AI-based pain assessment applications for patients, oncologists, and researchers. The first two sprints resulted in a functional prototype of the researcher application for structured data collection and the authentication and onboarding system for the patient application. While progress has been made, challenges in feature prioritisation and sprint planning have led to the postponement of certain functionalities. Future development will focus on completing the remaining components, integrating the AI module, and conducting usability testing. These steps are essential for moving towards usage in clinical research and potential implementation of AI-based pain assessment in oncology care.

5.6 Acknowledgements

The development of the AI-based pain assessment application was made possible through funding from the Gilead Foundation, a philanthropic initiative of Gilead Sciences, Inc (Grant nr: NL-2024-000358). This grant was awarded specifically to support the software development of the application, ensuring that the necessary technological infrastructure could be built to facilitate AI-assisted pain assessment.

The funding was secured through a grant application process, which included a written proposal and a presentation outlining the objectives, feasibility, and expected impact of the application. The application was submitted in collaboration with Innovattic (Delft, Netherlands), a company with expertise in digital health solutions. The initiators of the project had previously collaborated with Innovattic on related research initiatives, making them a suitable development partner for this endeavour.

Upon receiving the grant, financial resources were made available for the year 2025, enabling the project team to proceed with the development of the mobile and web applications according to the proposed timeline. This funding has been instrumental in supporting the technical implementation.

6 Database Development Study

This chapter presents the study protocol for a prospective clinical study to develop a high-quality, multimodal database of cancer patients experiencing pain. The primary goal is to collect audiovisual data – specifically facial expressions and vocal characteristics – together with clinical, demographic, and self-reported information to support the development of an AI-based automatic pain assessment model. The chapter outlines the background, protocol, setup, and ethical considerations. The protocol is currently under review by the ethics committee. Data collection is expected to begin in May 2025 at the Erasmus MC Cancer Institute, Rotterdam, the Netherlands.

6.1 Introduction

The automatic assessment of pain experiences and behaviours is a well-established research field aimed at enhancing personalised care, empowering patients, and supporting self-management in clinical context [30, 232, 233]. By leveraging advanced machine learning models, APA systems hold the potential to revolutionise pain management, but currently high-quality dataset for this purpose are lacking.

Despite the growing body of research in affective computing and the clear need for training and testing data, there remains a notable limitation in the availability of publicly accessible pain databases with (audio-)visual data. The few that are available, including the most frequently used

ones *i.e.* the UNBC McMaster Shoulder Pain database [234] and the BioVid heat pain database [235], suffer from significant shortcomings. These include small sample sizes, inadequate representation of chronic pain, limited diversity in patient demographics and environmental contexts, and a lack of multimodal data.

When searching for cancer-related pain databases the options become even more limited. Ideally, data for developing an AI-APA system for cancer patients would include cancer-related pain, which differs from non-cancer-related pain in its presentation and experience [236]. To the best of my knowledge, just one project group [221] published on the development of a cancer-related pain database with data of facial expressions, paralinguistics, and / or physiological measurements. This database, the Intelligent Sight and Sound (ISS) database [221], will provide facial expression and paralinguistic data from chronic cancer pain patients. While the ISS project is still in development, and only a fraction of the intended patient pool (29/112 (25.9%)) has been recruited, the database promises to be an important resource for future research in AI-based cancer pain assessment. However, until these types of comprehensive, multimodal datasets become more accessible, the advancement of AI-driven APA systems for cancer pain will remain limited.

To address this problem, we aim to develop a high-quality, multimodal cancer-related pain database that meet the needs and expectations of the scientific community. Therefore, the primary objective of this study is to create a training and validation database of short (no more than 60 seconds) audiovisual recordings (from the shoulders up) of cancer patients for the future development of an AI algorithm to assess pain in cancer patients based on audiovisual face and voice analysis. The estimated start date for inclusion is May 1, 2025.

6.2 Background

Table 6.1, adapted from the previously performed literature study (see separately provided document), summarises the seven identified publicly available pain databases used in APA research that contain data on facial expressions and/or vocal indicators of pain. Among the seven identified databases, three – SenseEmotion, EmoPain, and X-ITE Pain – contain both video and audio data.

Besides publicly available databases, the literature review identified three studies that used cancer-related pain data. Adibuzzaman et al. [237] collected images of 14 breast cancer patients in rural Bangladesh and 513 clinic-visit images of advanced cancer patients. Cascella et al. [238] recorded short interviews with cancer patients, capturing facial expressions and verbal reports. Wilkie et al. [239] developed a database that contains videos of facial expressions of lung cancer patients. Although these datasets might have contained interesting data, the datasets were briefly described, limited to video recordings, and not accessible for external researchers.

Table 6.1 Summary of available databases contain facial expressions and / or audio-recordings of subjects experiencing pain

Database	Subjects				Data		
	Participants	*Pain source*	*Type of pain and setting*	*Sample size*	*Modalities*	*Annotation granularity*	*Pain labelling*
SenseEmotion [240]	45 healthy subjects	Heat stimuli at 3 intensities with 30 repetitions 2 stimulus sites	Acute, experimental setting	8.1k seq.	Video of face, audio, EDA, ECG, EMG, RSP	Sequence level	Stimulus (calibrated per person)
EmoPain [241]	22 chronic lower back pain patients, 28 healthy controls	Physical exercises	Acute, experimental setting	50 seq.	Video, audio, EMG, MoCap	Sequence level	Self-report, OPI
X-ITE pain [242]	134 healthy subjects	Electrical and heat stimuli, each at 3 intensities	Acute, experimental setting	24k phasic + 804 tonic pain seq.	RGB-thermal video of face, RGB-depth video of body, audio, EDA, ECG, EMG	Sequence level	Stimulus (calibrated per person)
Delaware Pain Database [243]	240 healthy individuals	Potentially painful scenarios	Acute, experimental setting	229 images	Image of face	Frame level	FACS
UNBC-McMaster [234]	25 shoulder pain patients	Range of motion exercises with affected and unaffected limbs	Acute, experimental setting	200 seq.	RGB video of face	Frame level	FACS
						Sequence level	VAS, OPI
BioVid Heat Pain Database [235]	87 healthy subjects	Heat stimuli at 4 intensities with 20 repetitions at 2 sites	Acute, experimental setting	14k seq.	Video of face, EDA, ECG, EMG	Sequence level	Stimulus (calibrated per person)
MintPAIN [244]	20 healthy subjects	Electrical stimuli at 4 intensities with 40 repetitions in 2 trials	Acute, experimental setting	2k seq.	RGB, depth and thermal video of face	Sequence level	Stimulus (calibrated per person, VAS

Modalities BP: blood pressure, EDA: electrodermal activity, EMG: electromyogram, HR: heart rate, MoCap: motion capture, NIRS: near-infrared spectroscopy, RSP: respiration rate, SpO2: peripheral oxygen saturation rate Pain labelling FACS: facial action coding system, OPI: observer pain intensity, VAS: visual analogue scale

Across all identified databases, several key limitations persist for using those databases to develop an AI-based APA for cancer pain:

- Limited sample sizes: Most databases contain fewer than 100 participants, restricting model generalisability.
- Lack of multimodal data: The majority of datasets include only facial expressions, omitting vocal and physiological indicators.
- Focus on induced pain: Many datasets rely on controlled stimuli (e.g., heat, electrical pain) rather than spontaneous, clinical pain.
- Underrepresentation of cancer pain: Cancer-related pain is rarely included, despite its distinct characteristics and frequent occurrence.
- Restricted access: Many datasets remain unavailable for external researchers, limiting progress in AI-based pain assessment.

6.3 Methodology

6.3.1 Study Design and Setting

This study is a prospective, single-centre database development study conducted at the EMC Cancer Institute. The aim is to collect audiovisual recordings of cancer patients experiencing pain, along with relevant clinical and demographic information, to develop an AI-driven pain assessment model in a later stage of the project.

Patients will be recruited from the oncology ward of EMC and divided into two groups:

- Patient group – cancer patients admitted for cancer-related pain.
- Control group – cancer patients admitted for chemotherapy who report no pain.

The audiovisual recordings will be collected in a real-world, but controlled clinical setting, with patients filmed from the shoulders up. The patients are asked to perform two tasks that will be audiovisually recorded. Besides this, they are asked to self-report their pain intensity using the Visual Analogue Scale (VAS 0–10) and fill out a mood questionnaire (i-PANAS-SF [227] (and Dutch version [228])). Additional clinical data will be retrieved from the EMR.

6.3.2 Study Population

6.3.2.1 Inclusion Criteria

Participants must meet the following criteria:

- Aged 18 years or older.
- Diagnosed with cancer and admitted to the oncology ward of EMC.
- Patient group: Admitted for cancer-related pain (NRS $>$ 0).
- Control group: Admitted for chemotherapy, reporting no pain (NRS $=$ 0).
- Able to understand and provide informed consent.

6.3.2.2 Exclusion Criteria

Participants will be excluded if they:

- Are unable to provide informed consent.
- Have pain unrelated to cancer or its treatment.
- Have conditions that significantly affect facial expressions, such as neurological impairments, excessive dyspnoea, or severe drowsiness.

6.3.2.3 Sample Size

Machine learning algorithms typically require large datasets and likewise large sample sizes to increase the stability and generalisability of the model [245]. Currently, there is no formal method to determine appropriate pre-hoc sample sizes for machine learning algorithms [246]. The required sample size depends on the specific context, including the used prediction modelling method, number of features, the proportion of the predicted health outcome and the desired predictive performance as stated in the guidelines and quality criteria in the review of de Hond et al. [247]. Since the model architecture has not yet been decided, specific details on data requirements cannot be provided at this stage. However, based on closely related datasets that currently have been used, it can be expected that traditional machine learning models could achieve accuracies above 80% with approximately 200 audiovisual recordings. If a deep learning approach is chosen, significantly larger datasets will be required, as current datasets have proven too small for effective deep-learning model training (see the literature review and Chapter 2).

Beyond the need for sufficient data to develop a robust AI model, practical constraints and ethical considerations must also be considered. The principle of proportionality is particularly relevant here: data collection should be limited to what is necessary and justifiable, as excessive data collection consumes resources and, although small, places a burden on the participants. Therefore, it has been decided to do interim and posteriori evaluations of the sample size. For this evaluation a proof-of-concept AI model will be used. This model will be developed in parallel with the data collection for the database. Once data from 40 patients (excluding controls) is available, the initial interim evaluation will be conducted. The proof-of-concept model will then be trained and tested on the available data. The results of the model will be compared based on the data collected from different numbers of patients. If the results improve as more data is added, data collection and dataset expansion will continue. This process will be repeated with larger datasets until no further improvement is observed.

Since it could be expected that a dataset with about 200 audiovisual recording is enough and that with 200 admissions per year to the oncology ward for pain treatment optimisation all participants could be recruited in one year, the study aims to recruit 75 – 100 patients with cancer-related pain and 75 – 100 controls.

6.3.2.4 Recruitment and Informed Consent Procedures

Eligible subjects will be selected based on their reason for admission: for the patient group this is an exacerbation of cancer related pain; for the control group this is chemotherapy. Suitable patients will be identified by a dedicated researcher based on the admission description as stated in the EMR patient admission overview of the EMC oncology department.

To recruit the patients, the researcher will visit the identified patients in the oncology ward to ask them for their willingness to participate in this study. They will be verbally informed of this study's details by the researcher. The patient will also be provided with the information letter and informed consent form. After patients have been given at least 24 hours to read the informed consent form, the researcher will visit the patient again. The patient could ask questions and, if willing to participate, the patient could provide the signed informed consent form. The contribution of the patient ends when they no longer want to be filmed or when they are discharged from the hospital. Patients who are readmitted for pain management will not be filmed again.

Patients can withdraw their consent at any time for any reason. When a patient objects to the (re-)use of their data, at any point in time, after initially giving informed consent, the documented data for that patient, that has not yet been processed, will be deleted. Processed data cannot be withdrawn as it might compromise the reproducibility of the results obtained at that point.

6.3.3 Study Interventions

6.3.3.1 Clinical Protocol and Setup

Clinical Protocol

As part of standard care, hospitalised patients are routinely asked to report their pain multiple times per day, typically using the NRS. For the purpose of this study, audiovisual recordings will be made during one of these standard pain assessment moments. The researcher will position the recording setup

The researcher will set up the recording equipment in the patient's room, ensuring the environment is quiet, well-lit, and, where possible, has a consistent background to maximise recording quality. Once the setup is complete, the patient will be guided through the study-specific protocol (see Section 6.3.3.2).

Following completion of the recording, the researcher will securely transfer the audiovisual data to the protected digital storage environment of EMC, in accordance with the approved Data Management Plan (DMP). Once transfer is complete and data integrity is confirmed, the original recordings will be deleted from both the video recording device and the smartphone.

For patients in the control group, this procedure will be performed once. For patients in the other group, the recording will be repeated daily until the patient is discharged from the hospital.

Setup

The recording setup consists of a high-quality video recorder, a high-quality audio recorder, and a mid-range quality smartphone, enabling dual recordings, see Figure 28. In a later phase of the study, this setup will allow for an evaluation of how recording quality affects model outcomes, as well as an assessment of the feasibility of using smartphone cameras and audio recorders for audiovisual data collection. The video-recorder and audio-recorder are physically connected to allow for precise data synchronisation. A shared timecode system ensures that both modalities are

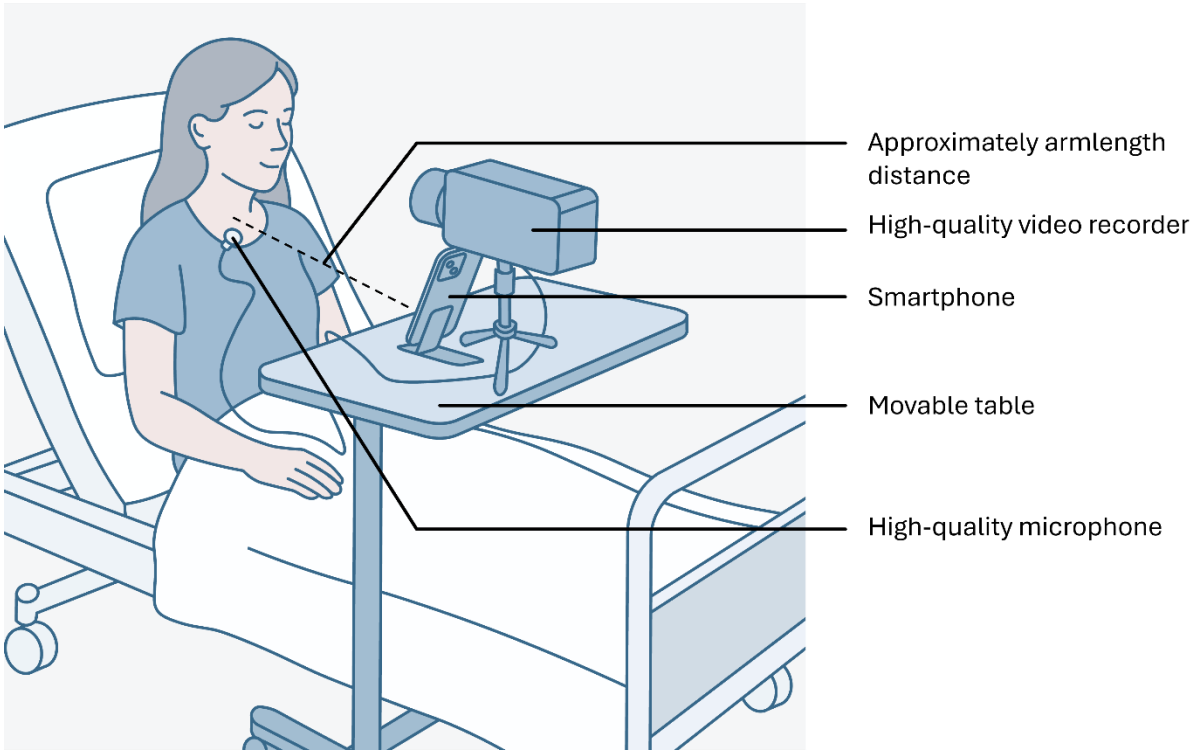

Figure 28 - Recording setup for the data collection in the hospital room of the patient

aligned accurately, preventing drift between the video and audio streams. This method enables seamless integration of multimodal data for analysis.

The patient will be asked to sit upright, which allows the researcher to position the recording setup. The recording setup is placed on a movable hospital table, which can slide over the patient's bed, ensuring a stable and adjustable recording position while maintaining patient comfort. Additionally, the mobility of the table allows the setup to be easily repositioned within patient rooms, adapting to different room layouts and bedside environments as needed.

The video-recorder and smartphone are positioned in a vertical stack, to minimize parallax effects. The video-recorder is placed on a tripod, while the smartphone is placed on a phone-holder. Although it might have been more representative to let the patient hold the phone, this would have created the risk of occluding the view of the video-recorder. The setup is positioned at the armlength of the patient, to mimic the use of the phone in their own hands, in a frontal position. For the same reason, the front camera of the phone is used.

For more information on the setup and equipment, see Appendices M and N.

6.3.3.2 Patient Protocol

Patients are asked to perform four tasks: 1) Provide their self-reported pain score, 2) Complete a mood-questionnaire, 3) Perform recording task 1 (prompt), and 4) Perform recording task 2 (narrative). Patients engage using a custom developed mobile application, that runs on the smartphone. The application is available in English and Dutch. Figure 29 provides a series of screens showing the different tasks in the application. Performing the four tasks will take approximately 3 minutes. When performing the first two tasks, the patient is allowed to take the smartphone in their hand. For the last two tasks the phone must be placed in the phone holder.

Self-reported pain score

First, the patient is asked to rate their pain score on a scale from 0, no pain, to 10, worst pain imaginable, by using a slider.

Mood-questionnaire

Second, the patient is asked to complete the i-PANAS-SF [227] (or Dutch version [228]) questionnaire. The patient will rate the applicability of 10 affective states on a 5-point Likert Scale, from 'not at all' till 'extremely'. This questionnaire assesses an individual's affect, which is useful since literature suggests that cancer patients experience complex emotions and beliefs that can influence their pain perception and, consequently, their clinical treatment [248, 249].

Recording task 1 - Prompt

Following the questionnaire, the patient is asked to read a 10 to 15 second passage aloud, when recorded by the cameras. The passage consists of a neutral text at a grade 3 reading level randomly selected. For example, the following passage will be used:

"The old man sat on the park bench, feeding the pigeons, unaware that one of them carried a tiny note tied to its leg."

Before the patient starts with the recording task, the patient is instructed to place their face within a frame of the scree and place their nose in the middle, indicated with a '+'-sign (see Figure 29 c/d).

When starting with the task, the patient is allowed to pre-read the text before the recording starts. When the patient is ready, the 'start recording' button must be pressed. This is also the sign for the researcher to start the recording of the other video-recorder. The patient will read the

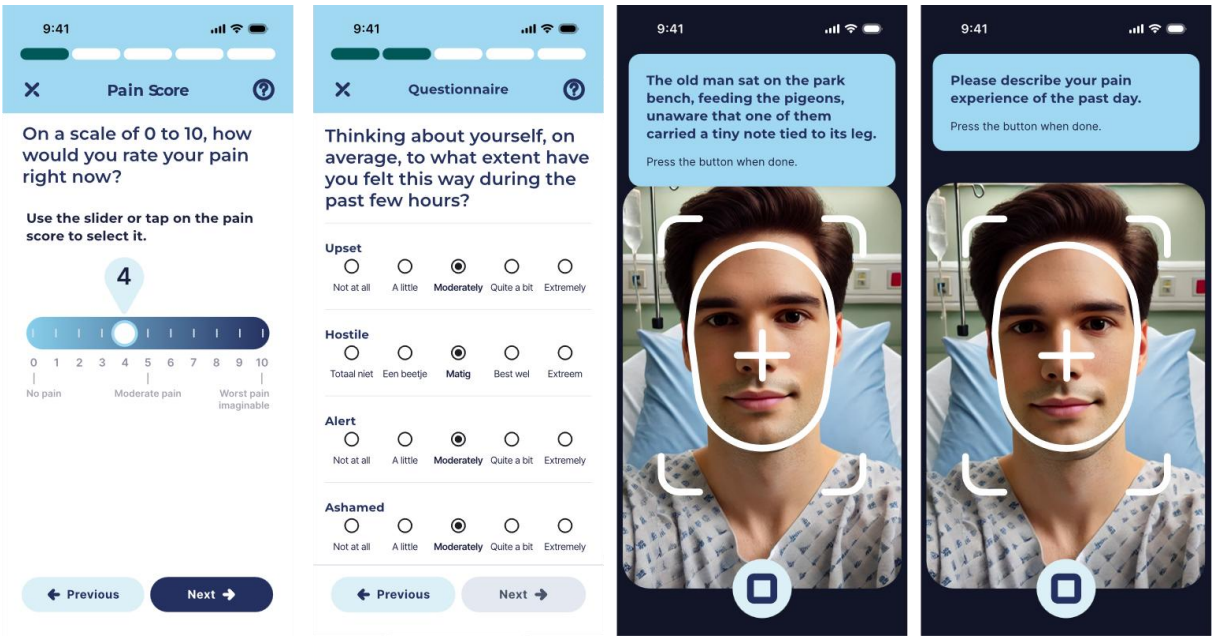

Figure 29 - Screenshots of the four elements of the patient tasks in the mobile application developed in collaboration with Innovattic, Delft, the Netherlands: a) Self-report pain score, b) Mood-questionnaire, c) Prompt recording task, d) Narrative recording task

passage aloud and press 'stop recording' if finished. After the recording the patient is asked whether the recording has to be redone, in case there was any disruption.

Recording task 2 - Narrative

Finally, in the second recording task the patient is asked to verbally describe their pain experience of the past day. Similar to the previous recording task, the recording instructions are shown before the recording, and patients could start and stop the recording themselves.

6.3.3.3 Researcher Protocol

Apart from newly created data, the researcher will retrieve several relevant parameters, see Section 6.3.4.2, from the patient's EMR and add it to the database by using the hospitals systems in place. The recordings of recording task 1 and 2 will be saved as separate entities.

6.3.3.4 Burden and Risks

Patients will be treated according to standard clinical care. There are no additional visits required and there is no additional burden associated with participation in this study, except for the 1-minute mood questionnaire.

The risk associated with participation in this study with respect to the safe storage of audiovisual data of face and voice samples of patients is limited but present, as patients are, by nature of the recorded audiovisual information, identifiable. This risk is limited by using a secure storage facility that fulfils all requirements of the GDPR and that is only accessible by the researchers associated with this project. All data is handled according to the data management plan.

6.3.4 Outcomes

The outcome of this study will be a dataset, that contains data of 150 – 200 adult cancer-patients with VAS-scores variating from 0 to 10, obtained in a controlled clinical environment.

6.3.4.1 Primary Study Parameters

The primary outcome parameters for this study are the VAS-score and the audiovisual recordings (.mp4/.avi/.wav-files, 30 frames per second) of the patient's face from the shoulders up and his/her voice when reading a prompt and describing their pain experience of the past day.

6.3.4.2 Secondary Study Parameters

The secondary outcome parameters are the outcomes of the i-PANAS-SF questionnaire and the parameters collected from the EMR: pain and affect measures (observer reported pain description, reported quality of life), analgesics in use (number of analgesics, drug names, dose, frequency), tumour specifications (type of cancer, stage, Karnofsky-score), general patient descriptors (age, sex).

6.3.5 Ethical Considerations

The study will be conducted according to the principles of the Declaration of Helsinki, Gedragscode Gezondheidsonderzoek 2022 and in accordance with other guidelines, regulations, and the General Data Protection Regulation (GDPR).

Ethical approval for the study is requested from the Medical Ethics Commission of the EMC and expected to be obtained by the beginning May, 2025.

All participants were provided with detailed information about the study, including its objectives, procedures, and potential risks by providing a participants information letter and verbal explanation. Participants were required to give written consent before participation.

Results will be published in a relevant scientific journal and communicated to participants and relevant institutions.

6.3.6 Data Storage, Privacy and Accessibility

Given the sensitive audiovisual recordings that are collected, strict measures have been set in place to ensure patient privacy and compliance with legal and ethical guidelines. The audiovisual recordings inherently contain personally identifiable information, making them subject to strict data protection regulations.

Ensuring the security and confidentiality of participant data is a critical aspect of this study. Therefore, the following measures have been implemented: 1) consultation with the data stewards, privacy contact persons, chief information security officer, privacy knowledge organisation and legal representative, 2) development and thorough review of a data management plan, and 3) completion of a data protection impact assessment. For the data management plan and the data protection impact assessment, the researcher could be contacted.

All collected audiovisual and clinical data will be handled in compliance with GDPR guidelines and institutional data management policies.

All audiovisual recordings will be securely stored on the Research IT – Storage & Compute platform at EMC. Immediately after collection, data will be transferred from the recording devices, which are protected by encryption, to this secure storage system. Once successfully transferred, the original files will be deleted from the recording devices to prevent unauthorised access.

Access to stored data will be strictly restricted to authorised research personnel. Only the researchers who are part of the research team will have access to the data. Access to the data will be managed by the principal investigator. Team members will be denied access to the data as soon as they are no longer part of the research team. New team members will only be given access to the data by the principal investigator if their role in the investigation requires access to the data.

Given the identifiable nature of audiovisual recordings, the raw video and audio data will not be made publicly available. However, considering the scarcity of open datasets for AI-based pain assessment, a secondary, anonymised version of the dataset will be created after development.

This version will consist of extracted features from the audiovisual recordings using widely used toolkits such as OpenFace [219] (facial features) and OpenSMILE [124] (vocal features). These features are not directly traceable to individuals, enabling broader scientific use while safeguarding patient privacy. Access to this processed dataset will be granted to non-profit academic researchers upon request and approval by the principal investigator. The data will be archived in a certified repository such as DataverseNL and described using standard metadata schemas (e.g. DublinCore), with persistent identifiers (DOI) to ensure findability and traceability. The anonymised dataset is expected to be made available to academic researcher after the AI-model development phase has been concluded.

Data will be stored for 10 years in accordance with EMC's data management policies.

6.4 Discussion

This protocol outlines a novel approach to developing a high-quality, multimodal dataset for AI-based pain assessment in cancer patients. By collecting audiovisual recordings alongside clinical and self-reported data in a controlled hospital setting, the study aims to address a critical gap in current affective computing research. The focus on cancer-related pain – a complex and underrepresented condition in existing datasets – adds important clinical relevance.

The study protocol was designed to balance scientific value with practical feasibility. Within this protocol patients are asked to complete four tasks: a VAS score, a mood questionnaire, and two short audiovisual recordings. While this structure allows for standardised and efficient data collection, it does not yet include information on the impact of pain on daily life or the patient's tolerability of pain – dimensions that were highlighted as clinically meaningful in the conceptual framework of the tool presented in Chapter 4. At the time the protocol was submitted for ethical approval, those insights were not yet available because the interview study was still conducted. However, in light of the insights gained since, it should be considered whether these additional parameters could be included in a future protocol amendment to further enhance the clinical relevance of the dataset.

Other practical considerations may emerge during implementation. While the protocol was designed to ensure adaptability across clinical settings, differences in patient room layout and environmental conditions may influence recording quality. Moreover, although the sample size estimates are informed by literature, they will be evaluated iteratively using a proof-of-concept AI model to ensure the final dataset is both robust and proportional to its intended use.

Lastly, the dual-recording setup using both high-end and mid-range devices offers an opportunity to explore how recording quality influences model performance. This is especially relevant for assessing whether smartphones could serve as a feasible data source in future patient-facing applications. However, as the final equipment selection is still pending, this aspect of the study remains subject to refinement.

Overall, this protocol provides a strong foundation for creating a unique, clinically meaningful dataset. As the study progresses, flexibility, reflexivity, and a commitment to integrating emerging insights will be essential to ensure the dataset meets both scientific and clinical needs.

6.5 Conclusion

This chapter has outlined the study protocol made for the development of a high-quality, multimodal database of cancer patients experiencing pain. The study aims to collect recordings of facial expressions and vocal characteristics, alongside clinical and demographic data, to support the development of an AI-based automatic pain assessment system. A prospective, single-centre approach is employed, with data collection taking place in a controlled clinical environment at Erasmus MC. Ethical approval is currently pending, but data collection is expected to begin on May 1, 2025.

A carefully designed methodology ensures that the dataset is representative, reliable, and ethically obtained and in line with the requirements for a high-quality dataset for machine learning algorithms. By creating one of the first dedicated cancer pain audiovisual databases, this study addresses the critical gap in available datasets and provides a foundation for future AI-driven advancements in pain assessment. The resulting dataset will not only contribute to improving pain management for cancer patients but also advance the broader field of affective computing and automated healthcare solutions.

7 Conclusions and Recommendations

7.1 Overview

This thesis presented the initial steps towards the development of a human-centred, AI-empowered tool for the automatic assessment of cancer-related pain. Recognising that methods used in current clinical practice – particularly in the outpatient oncology - are limited in their ability to capture all patients experiencing pain and also come with several challenges, this research project was started to address the question whether HCAI technologies might enhance both the accuracy and usability of pain assessment in this context.

To investigate how AI could support pain assessment, this thesis adopted a user-centred, multiphase design process inspired by the Double Diamond framework. The project moved through the phases of discovering the broader problem space, defining the specific design focus, developing a conceptual framework, and initiating the first steps of technical development.

During the discovery phase, background research was conducted to examine the current state of cancer-related pain assessment. This involved familiarisation with key literature on the multidimensional nature of pain, the methods used in clinical practice, and the technical possibilities of APA. In addition, an exploratory interview study with medical oncologists at the EMC provided in-depth insight into how pain is assessed in practice, sometimes deviating from

standard protocols. Moreover, thematic analysis revealed significant challenges in the current pain assessment and management process: the complexity and subjectivity of pain, ambiguity in responsibility for addressing pain, communication and interpretation barriers, balancing all types of information with clinical judgement, and practical barriers. These insights were supported by existing literature and trends in medicine and formed the foundation for the next phase of the project.

In the definition phase, expert consultations were used to refine the problem focus and guide the development of the tool concept. The second part of the interview study explored oncologists' attitudes towards the idea of an AI-based pain assessment application, using the mTAM as framework. It was found that the oncologists are interested and perceive the potential value of such a tool – but only under specific conditions. They emphasised the need for clinical validation, contextual interpretation, integration with existing workflows, and a design that supports rather than replaces human judgement.

Building on these insights, the development phase focused on creating a structured conceptual framework for the APA model and tool, to be used in the next separate parts of the technical development phase. Through expert workshops, design brainstorming, insights from the earlier research phase and assumptions on feasibility, the concept crystallised around three core functionalities: 1) data collection via using a mobile application for patients, 2) AI-based pain prediction that categorises pain, and 3) feedback mechanisms for both patients and clinicians. These components were integrated into a modular architecture that allows for future technical expansion and clinical adaptation.

Concurrently, two development tracks were initiated. First, in collaboration with the software development company Innovattic, the design and technical implementation of the APA tool were initiated using agile development sprints. As product owner, I coordinated the design goals and ensured alignment with the research aims. After two sprints, the researcher application is nearly ready to be used in the database development study. Besides this, first efforts are made on the patient application development, and the prototype will soon be tested with cancer patients recruited through NFK. Second, a study protocol was developed for the database development study, which will support the creation of a high-quality, multimodal dataset. Ethical approval is underway, and data collection is scheduled to begin in the coming months.

Together, these efforts represent the initial steps toward a clinically relevant and technically feasible AI-based APA tool for cancer patients. By integrating stakeholder insights, expert guidance, and iterative development, this thesis has laid a strong interdisciplinary foundation for the continuation of the SENSAI project. While the technical implementation of the AI model itself lies beyond the scope of this thesis, the work presented here demonstrates the viability and importance of developing such tools in close alignment with clinical realities and end-user needs. In doing so, it lays the groundwork for a novel approach to pain assessment in oncology – one that has the potential to improve how pain is recognised, monitored, and ultimately managed in clinical practice.

7.2 Key Limitations

While this thesis provides a coherent foundation for the development of a clinically relevant and user-centred APA tool, several key limitations must be acknowledged.

First, although the exploratory interview study provided valuable insights into current pain assessment practices and oncologists' attitudes, the data reflects only the first half of the planned study. Interviews with patients are still ongoing and therefore not yet included, limiting the completeness of the thematic analysis and resulting in an unbalanced view of stakeholder needs. Consequently, the design process did not yet incorporate direct input from patients, constraining the extent to which usability, acceptability, and lived experience could be embedded in the early development. While initial steps toward patient involvement have been taken, broader engagement will be essential in subsequent phases.

Second, the qualitative findings are based on interviews with a small group of oncologists from a single academic medical centre. While insightful, this limited sample lacks diversity in institutional setting, clinical role, and geographical region, reducing the generalisability of findings to other oncology contexts, particularly those outside tertiary care.

Third, several components of the conceptual framework—such as the selected functionalities, measurement tasks, and feedback mechanisms—were based on expert consultation, literature, and anticipated feasibility. However, these assumptions have not yet been empirically tested. The measurement protocol—referring to the defined procedures for collecting patient data, including task structure, timing, and contextual inputs—is still under development, and no usability testing of the application has yet been conducted. As such, the framework should be viewed as an initial concept that requires further validation and refinement.

Moreover, although the design process was informed by literature, expert input, and exploratory interviews, structured iteration across stakeholder groups was limited. Design decisions were primarily shaped within the research group and iterated through software development sprints, without formally revisiting earlier stages in response to new feedback. Given the exploratory nature of this phase, this is understandable; however, future development should include more extensive, cross-stakeholder iteration to strengthen the user-centred approach.

Finally, several project components were initiated but could not be completed within the scope of this thesis due to time constraints, staged funding, and dependencies such as ethical approval. These include the development of the multimodal database, patient testing of the application, and the implementation of the measurement protocol. In addition, the transition of the project into a PhD trajectory led to a strategic shift in priorities: instead of completing a single part in full, the focus was placed on initiating and aligning multiple components to ensure continuity and readiness for further development in the next phases of the SENSAI project.

7.3 Recommendations

7.3.1 Continuation of the Project

Based on the findings and limitations of this thesis, several recommendations can be made to guide the next phases of the SENSAI project. These recommendations span ongoing clinical research, technical development, model design, and publication.

7.3.1.1 Integrate Patient Perspectives into Design and Evaluation

To ensure the tool aligns with the needs, preferences, and capabilities of its end users, patient involvement should be prioritised in upcoming stages. The continuation of the interview study with cancer patients will be crucial to better understand how patients experience pain communication and how they view the potential role of AI in supporting it. In parallel, usability testing of the patient-facing application should be conducted with a diverse patient group to evaluate feasibility, burden, and user experience. Insights from these activities should inform iterative refinements to both the user interface and the measurement protocol. In the longer term, a study should be conducted to examine the impact of the APA tool on pain management practices, patient-clinician communication, and patients' self-reflection or learning about their own pain patterns. Such a study would provide insight into the broader clinical and behavioural value of the tool beyond its predictive performance.

7.3.1.2 Finalise and Evaluate the Measurement Protocol

Beyond design considerations, the measurement protocol should be clearly defined in terms of frequency, conditions, and required inputs, using both expert feedback and empirical testing. Key considerations include balancing the richness of data with patient burden, avoiding sampling bias, and ensuring consistency across recordings.

7.3.1.3 Continue and Expand Application Development

The development of both the patient mobile application and the researcher application should continue, with a focus on building stable, fully functional prototypes. For the patient application, priority features include audiovisual recording, integration of pain and mood questionnaires, and secure data transfer. The researcher-facing application should support participant management, structured data review, and linkage with anonymised clinical information.

In addition, the possibility of developing a web-based interface for oncologists should be further explored. Such an interface could allow clinicians to view relevant patient-reported data and model outputs within their workflow. However, the feasibility of this feature – particularly with respect to funding, integration, and clinical priorities – requires further assessment.

Iterative testing and refinement of the patient application should be informed by user feedback. Particular attention should be given to digital literacy, emotional burden, clarity of instructions, and patient preferences regarding notification frequency and task scheduling, to ensure high usability and long-term engagement.

7.3.1.4 Start and Support the Database Development Study

With ethical approval in progress, the data collection study should be initiated as soon as possible to build a high-quality, representative, and diverse multimodal database. Quality control procedures should be implemented to handle variability in recordings and ensure proper synchronisation of modalities. Metadata such as pain type, affective state, and contextual factors should be consistently captured. To ensure efficient and feasible data collection in clinical settings, the project team should consider involving additional colleagues or student assistants. Expanding the team in this way would help distribute the workload and support a more systematic, consistent, and timely data collection process.

7.3.1.5 Develop and Refine the AI Model

The technical development of the AI model should proceed in parallel with data collection. An initial proof-of-concept model may be developed using early data from the project-specific database to explore suitable modelling strategies and prepare for pipeline integration. Once the full dataset is available, a full-scale model can be trained and evaluated. Studies should be conducted to examine how technical variables—such as device quality, background noise, and lighting—affect model performance. In addition, the value of contextual data (e.g., mood, pain interference, time of day) in improving prediction accuracy and relevance should be explored.

In addition, explainability should be a key focus from the outset: research into explainable AI techniques will be important for supporting clinical acceptance and trust.

7.3.1.6 Plan for Long-Term Implementation and System Integration

As the project progresses, early planning for integration into clinical systems will be essential. This includes exploring how the APA tool can eventually be embedded into platforms such as DigiZorg and linked with EMRs, while ensuring that patient data remains secure and privacy regulations (e.g. GDPR) are upheld. Close collaboration with IT and AI departments, hospital systems, and legal/ethical advisors should begin in parallel with technical development to avoid delays during the implementation phase.

7.3.1.7 Interdisciplinary Collaboration

the success of the project will depend on sustained interdisciplinary collaboration. Ongoing engagement with clinicians, developers, AI researchers, and patient representatives is vital to ensure the tool remains clinically relevant, technically robust, and ethically sound. This also includes the collaboration with the Intelligent Sight and Sound research group, who are currently working on the development of a multimodal cancer-related pain database. The ISS group has expressed interest in continued collaboration, and there are clear opportunities for knowledge sharing and mutual support between the SENSAI project and their work.

7.3.1.8 Share Findings Through Scientific Publication

To contribute to the broader scientific and clinical discourse, relevant parts of this thesis should be prepared for publication. This includes the findings from the earlier performed technical

literature study, the current exploratory interview study, the scheduled user-tests and the ultimate results database development study. Publishing in interdisciplinary journals focused on digital health, oncology, or medical AI will help position the SENSAI project within the academic field and enable early peer feedback, collaboration opportunities, and visibility within the clinical and research communities.

7.3.2 Future Research

While the SENSAI project will continue to develop and evaluate the APA tool within a defined clinical and technical framework, several broader research directions remain open for future exploration beyond the scope of this project.

7.3.2.1 Explore Alternative Modelling Strategies

Future research could investigate the use of alternative modelling strategies to capture the complexity of subjective pain experiences. This includes probabilistic or ordinal regression models, clustering techniques, or semi-supervised learning methods that do not rely solely on traditional self-report scales. Such approaches may help address the limitations of binary classification and better reflect the multidimensional nature of pain.

7.3.2.2 Integrate Additional Data Modalities and Sources

Beyond audiovisual input, future APA models may benefit from the integration of additional data sources, such as wearable sensor data, EMR-derived clinical information, or patient-reported outcomes collected through other digital tools. Multimodal fusion techniques could support a more comprehensive understanding of pain and its interaction with physiological, behavioural, and contextual factors.

7.3.2.3 Large Language Models for Pain Interpretation

While verbal descriptions were not yet included in the AI model in this thesis, future research could explore the use of large language models to analyse spoken or written pain narratives. This may help simulate aspects of clinical reasoning and improve the interpretability of patient-reported experiences.

7.4 Conclusion

This thesis presented the initial steps toward the development of a human-centred, AI-empowered tool for the automatic assessment of cancer-related pain. Through a multiphase design process, it explored the challenges of current clinical pain assessment, examined oncologists' attitudes toward the concept, proposed a conceptual framework for the APA tool, and initiated its technical development. While several components remain in progress, the project has established a strong interdisciplinary foundation for future research and development. By aligning technical innovation with clinical realities and stakeholder input, this work contributes to the broader ambition of improving how pain is recognised, communicated, and managed in cancer care.

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Appendices

A Protocol Cancer-Related Pain Erasmus MC

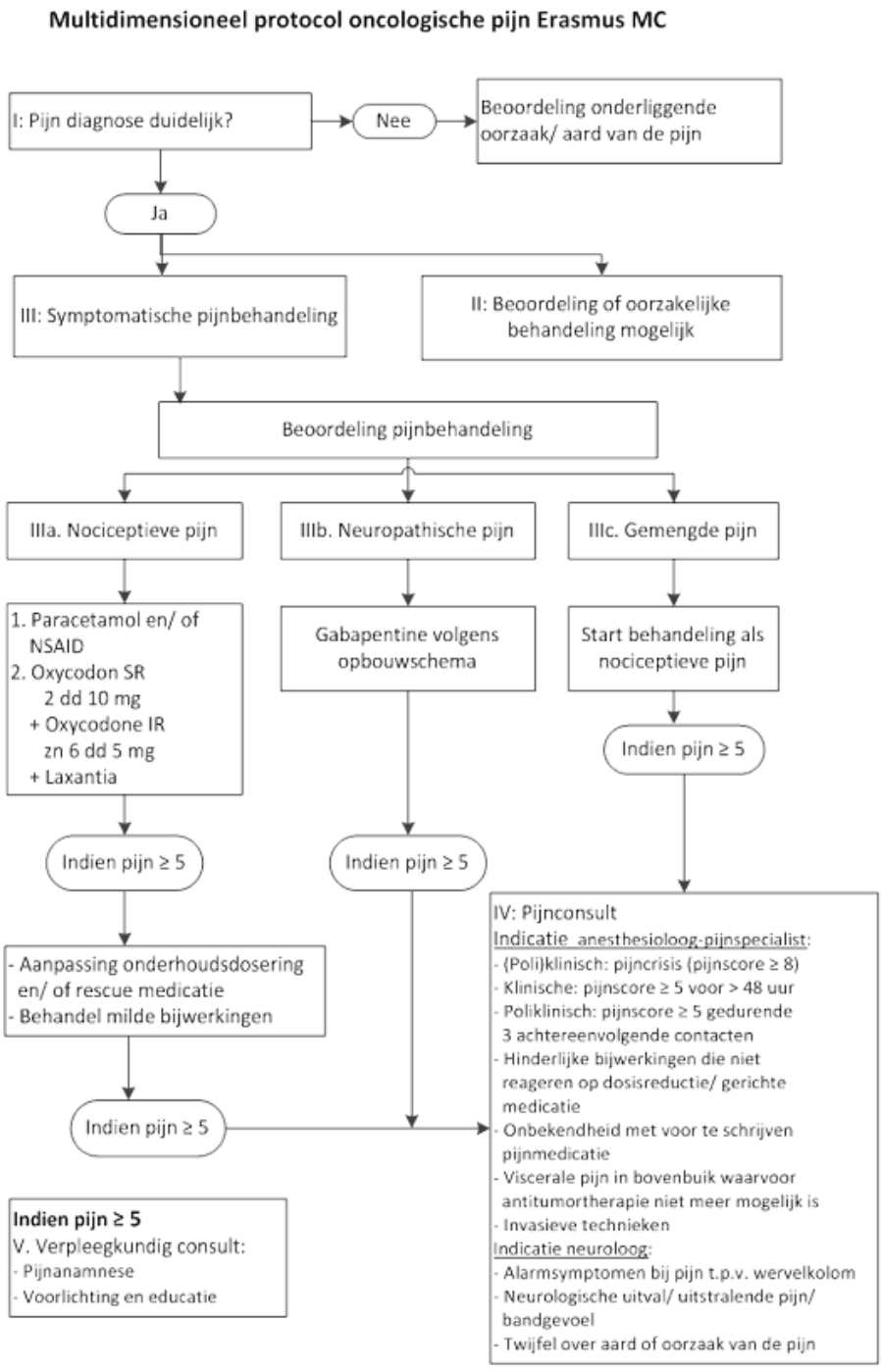


Figure 30 Protocol for treating cancer-related pain in the Erasmus Medical Centre [85]

B Standards for Reporting Qualitative Research

O'Brien et al. [168] formulated and defined standards for reporting qualitative research, aiming to improve the transparency of all aspects of qualitative research. The checklist that was developed was used in this study, see Table B.1.

Table B.1 Checklist for Standards for Reporting Qualitative Research

Item	Description	Page Number
Title and Abstract		
Title	Concise description of the study's nature and topic; recommended to identify the study as qualitative or indicate the approach or data collection methods.	- *
Abstract	Summary of key study elements following the intended publication format, including background, purpose, methods, results, and conclusions.	- *
Introduction		
Problem formulation	Description and significance of the problem/phenomenon studied, review of relevant theory and empirical work, and problem statement.	38-39
Purpose or research question	Purpose of the study and specific objectives or questions.	40
Methods		
Qualitative approach and research paradigm	Description of the qualitative approach (e.g., ethnography, grounded theory) and guiding theory if applicable. Identifying the research paradigm (e.g., postpositivist, constructivist) is recommended, along with a rationale.	44-
Researcher characteristics and reflexivity	Influence of researchers' characteristics (e.g., personal attributes, experience, assumptions) on the study and interaction with research questions, approach, methods, results, and transferability.	- *
Context	Description of the study setting and salient contextual factors, with a rationale.	44-45
Sampling strategy	Explanation of participant, document, or event selection, including criteria for stopping data collection (e.g., saturation), with a rationale.	44-45
Ethical issues pertaining to human subjects	Documentation of ethics review approval, participant consent, confidentiality, and data security issues.	45

Data collection methods	Types of data collected, details of procedures (e.g., start/stop dates, iterative process, triangulation, adaptations during the study), with a rationale.	45-48
Data collection instruments and technologies	Description of instruments (e.g., interview guides, questionnaires) and devices (e.g., audio recorders) used, and any changes made over the study.	46
Units of study	Number and characteristics of participants, documents, or events included, and their level of participation.	49
Data processing	Methods for processing data before and during analysis (e.g., transcription, coding, anonymization, verification of data integrity).	48-49
Data analysis	Description of how inferences, themes, and conclusions were developed, including involved researchers and approach references, with a rationale.	48-49
Techniques to enhance trustworthiness	Description of techniques used to improve trustworthiness and credibility (e.g., member checking, audit trail, triangulation), with a rationale.	49
Results/Findings		
Synthesis and interpretation	Main findings, including interpretations, themes, and integration with prior research or theory. May include theory or model development.	49-74
Links to empirical data	Supporting evidence (e.g., quotes, field notes, text excerpts, photographs) for analytic findings.	49-74
Discussion		
Integration with prior work, implications, transferability, and contribution(s) to the field	Summary of findings, connection to prior research, implications, generalizability, and unique scholarly contributions.	75-79
Limitations	Discussion of study trustworthiness and limitations.	79-81
Other		
Conflicts of interest	Disclosure of potential sources of influence or perceived influence on the study and how they were managed.	82
Funding	Description of funding sources, other support, and the role of funders in data collection, interpretation, and reporting.	82

* This section is currently omitted due to the structure of the thesis or because it is presumed known to the reviewers; however, it will be included in any future publication of the study.

C Operationalisation of Constructs

Table C.1 Original definitions and applied definitions

Construct	*Definition*	*Reference*	*Applied Definition*	*Response*
Attitude towards Using (ATU)	The degree to which a person has a favorable or unfavorable evaluation of the use of a particular system	Ajzen [250]	The overall positive or negative evaluation that a participant holds regarding the use of the AI-based pain assessment tool.	Response category: positive / negative / neurtral Content: considered influential factors
Behavioural Intention (BI)	The degree to which a person is motivated or willing to extert effort to perform the target behaviour	Davis [148]	The likelihood that a participant intends to use the AI-based pain assessment tool in the future.	Response category: positive / negative / neurtral Content: considered influential factors
Perceived Usefulness (PU)	The degree to which a person believes that using a particular system would enhance his or her job performance	Davis [148]	The participant's belief about whether the AI-based pain assessment tool will be advantageous to him/her.	Response category: positive / negative / neurtral Content: considered influential factors
Perceived Ease of Use (PEOU)	The degree to which a person believes that using a particular system would be free from effort	Davis [148]	The participant's belief about whether the AI-based pian assessment tool will be free of effort.	Response category: positive / negative / neurtral Content: considered influential factors
Trust (T)	The belief that the other party will behave responsibly and will not attempt to exploit the vulnerabilities of the user.	Pavlou [251]	The participant's belief that the system will operate responsibly, fairly, and without exploiting the vulnerabilities of patients or clinicians.	Response category: positive / negative / neurtral Content: considered influential factors
Perceived Risks (PR)	The users' subjective evaluation of incurring losses while using a particular system	Pavlou [251]	The participant’s perception of uncertainty and potential negative consequences associated with using the AI-based pain assessment tool, such as concerns about accuracy, privacy, or treatment impact.	Response category: positive / negative / neurtral Content: considered influential factors

D Interview Guides

Two protocols for conducting the semi-structured interviews with oncologists and patients were developed. The content of the questions was inspired by literature, MM's and MK's experience with cancer patients, oncologists and hospital workflows, and HT's experience with qualitative methods. For the part on the TAM, inspiration was drawn from the methodology of Oviedo-Trespalacios et al. [252].

The interview protocols ensured that all important context was mentioned, and the required open questions were asked, while also providing the flexibility to further explore the participant's responses.

The interview questions for the oncologists are shown in Section D.1. For the full interview protocols for the oncologists and patients, see the additional provided documents.

D.1 Oncologists

The questions asked during the interview are retrieved from the interview protocol for oncologists and ordered by part of the interview and construct. For the order of the questions, the full interview protocols could be accessed. A further remark: In the interview protocol questions on design and implementation preferences (part 5) were asked when the construct was discussed during part 4 to improve the flow of the interview. In order to present the questions as how they were asked, some of the questions with a topic on design and implementation preferences are presented in Table D.1.

Table D.1 Interview Guide

Construct	*Questions*	*Follow-up questions and prompts*
Part 1 Current Pain Assessments Methods		
	Can you describe how you typically assess pain in your patients?	What methods or criteria do you use?; How often do you discuss pain? Often, regularly, sometimes, rarely?; How often do you perform a pain assessment using a standardised method such as VAS or NRS? Often, regularly, at every visit?; And which method do you use?; Do you or the patient usually initiate the conversation about pain?; Is there a difference in how you assess pain in hospitalised versus non-hospitalised patients?
	How do you obtain information about your patient's pain experience if they are not hospitalised?	Does this information help improve care in your opinion (if already used), or do you think it could help improve care in the future (if not yet used)?
	Have you ever experienced differences in how different groups of people express their pain to you?	For example, different groups could refer to gender, Dutch vs. non-Dutch speakers, cultural differences, etc.
	How do you use the patient's pain description in the care you provide?	Do you always use the pain description in the same way?; Are there factors that make you weigh the patient's description more or less heavily?
	When you make a change in the pain treatment strategy, how do you then monitor its effects?	How and when do you check whether it was successful?

Have you ever felt that your pain management approach/treatment was not fully aligned with the patient's needs?	Either too much or too little?; Can you share how this happened and how often you experience something like this?
Part 2 Challenges experienced during the current pain assessments	
What challenges do you encounter when gathering information about your patients' pain levels?	What are the main obstacles?; Where do these challenges stem from? And how do you experience this?
Are there specific situations in which you find it particularly difficult to evaluate a patient's pain?	Do you experience additional or different challenges when assessing and monitoring pain in non-hospitalised patients?
Are there certain patient groups that pose more challenges in pain assessment?	For example, elderly patients, cognitively impaired patients.
How do you handle the challenges you experience in evaluating a patient's pain?	How do you handle situations where patients struggle to communicate their pain effectively?
Do you think the current pain assessment methods provide enough information to make treatment decisions?	Do you think these assessments are accurate enough and performed frequently enough to represent the patient's pain experience and adjust care accordingly?; What do you do to ensure an assessment is accurate?; Do you have examples?
To what extent do you rely on the patient's self-reported pain assessment when making treatment decisions?	Have you ever experienced situations where there was a noticeable difference between what the patient reported and what you observed in terms of pain intensity?; How do you handle such a situation?
Part 3 Potential Solutions for Current Challenges	
What do you think could help improve pain assessment?	Are there tools, techniques, or practice changes you can think of for this? Whether existing or not yet developed?; If there were a perfect tool to help with pain communication, what would it ideally help to understand about your patients' pain?

	Can you think of other potential improvements for pain assessment and treatment for patients in an outpatient setting?	
Part 4 Attitude towards an AI-based Pain Assessment Tool		
Attitude towards Using	What are your first thoughts when you hear about this technology?	
	How would you like to receive the results of the application?	Through the patient, via a portal, integrated into the EHR?
	What do you think of using such an AI tool to help assess patient pain?	
	Do you think technology like this will make pain assessment different?	In what ways?; Under which circumstances?
	How do you think your colleagues and other healthcare providers would view the use of this technology?	
Behavioural Intension	If the technology were available, how likely is it that you would use it in your practice?	
	Do you see yourself using this tool in the long term?	
	What would it take to do that?	
	How do you envision such a tool being used?	What is needed to use the tool?; Do you think the tool could be used in an inpatient and outpatient setting?
Perceived Usefulness	How useful do you think this tool could be in your work?	
	How do you think this application could support your work in assessing pain in your patients?	In what ways?; Under which circumstances?; In an inpatient and outpatient setting?
	Will it serve a purpose for you?	
	To what extent do you think an automatically generated pain assessment could contribute to better treatment decisions?	
	Do you see potential benefits in integrating such a tool?	Think about benefits for both you and the patient; Do you think the use of this application could improve communication about pain with your patients?; Are there specific patient groups that you think this tool would be most valuable for?
Perceived Ease of Use	Do you think the tool will be easy to use?	Both for you and the patient
	Do you think it will be easy to integrate the tool into your daily practice?	Are there factors that could help with this?
Trust	Do you think you would trust the pain assessment from this tool?	Why or why not?; What factors could help with this?; What do you see as requirements for you to trust it?

Perceived Risks	Do you see any potential concerns or risks with integrating such a tool into your practice?	
	Do you think this tool has certain limitations for specific patient groups?	
Part 5 – Design and Implementation Preferences		
	What do you find important in the design of the user interface of this application?	Both for patients and healthcare providers?
	How would you prefer to see the information generated by the app presented?	For example, in the form of graphs, an overview of pain scores, or a summary?
	How important is it for you that the application can be linked to existing systems such as the electronic health record (EHR)?	
	Are there any additional features you can think of that you would find important for the application?	What are functionalities or aspects of the application that could make it useful or more useful?
	What do you find important in the design of the user interface of this application?	Both for patients and healthcare providers?

E Transcription Protocol

This appendix outlines the transcription protocol used to process and analyse the semi-structured interview data collected during the exploratory study. The protocol was designed to ensure consistency, accuracy, and completeness in capturing participants' responses while maintaining confidentiality.

E.1 General Guidelines

- Verbatim Transcription: All interviews are transcribed word-for-word, including verbal hesitations, repetitions, and false starts.
- Exclusions: Filler words (e.g., "uh," "um") and non-verbal sounds (e.g., coughing, laughing) are excluded unless deemed contextually significant.
- Pauses: Pauses are marked to capture the natural rhythm of the conversation:
    - Short pauses (approximately 1 second) are marked as ((.)).
    - Long pauses (several seconds) are marked as ((...)).
- Unfinished Sentences and Interruptions: "..." are used to indicate an unfinished sentence. If the reason for the interruption is relevant, this is included in brackets [ ] for clarity.
- Non-Verbal Descriptions: Actions or visual cues referenced by participants or the interviewer are noted in square brackets [ ]. For example: [points to the document].
- Inaudible Segments: Words or phrases that are unclear are marked as [inaudible (X words)], where "X" indicates the estimated number of inaudible words.
- Foreign Language Words: Words or phrases spoken in English (or any language other than Dutch) during the interview are marked in *italics* to indicate that they were spoken in a different language.

E.2 Formatting Rules

- Time Stamps: Time stamps are added at the start of a new paragraph when a new speaker started talking. The format that is used is [hh:mm:ss]. It indicates the exact time in the recording.
- Speaker Identification: Each speaker is clearly identified at the start of their dialogue, for example "Interviewer", "Oncologists", or "Patient".
- Paragraphing: Each speaker's response is transcribed as a new paragraph for clarity.
- Consistency in Notation: Uniform abbreviations and symbols (e.g., ((.)), [inaudible]) are used across all transcripts.

Box B Example of the Application of the General Guidelines and Formatting Rules

[00:05:01] Interviewer
How often do you talk about pain with your patients?
[00:05:03] Oncologist
Every time I see a new patient, ((.)) or when I am aware of a pain problem, I discuss ... [phone of the oncologist rings, recording is paused]

E.3 Confidentiality Measures

- Anonymisation: Personal identifiers (e.g., names, locations, or specific medical details) are replaced with descriptive placeholders to maintain participant anonymity and maintain the importance of that reference. For example: "Dr. Smith" was replaced with [Name of colleague 1].
- Secure Storage: All transcripts are stored in encrypted digital files on a secure server accessible only to authorised research team members.

E.4 Quality Control

- Proofreading: Each transcript is reviewed by the transcriber for errors or omissions.
- Cross-Checking: A second researcher independently checks a random subset of transcripts to ensure consistency with the audio recordings.

F Pain Assessment Process Mapping

F.1 Interactions Mapping

The pain assessment process for an oncologist focuses on gathering information about the patient's pain state to guide pain management decisions and ultimately improve the patient's pain experience. To obtain this information, oncologists interact with patients, other healthcare providers, important others for the patient and digital systems. Given the central role of information gathering in pain assessment, the oncology department (and hospital in general) offer various ways for patients to report their pain. During interviews with oncologists, several interactions were identified through which patients can communicate their pain experiences. Important interactions that were identified for the oncologist and patient were systematically mapped in Figure 32 and more illustratively in Figure 31.

The interactions the patient could have regarding their pain experience could involve:

- Interaction with their important others: Patients may discuss their pain experience with family members, friends, or caregivers who provide emotional support, assist with pain management strategies, or help communicate their symptoms to healthcare professionals. Important others might encourage the patient to report their pain accurately, help track changes in symptoms, or advocate for adjustments in treatment.
- Interaction with their general practitioner: The GP may be the first point of contact for managing pain before referral to oncology. They assess pain severity, prescribe pain medication, adjust treatment when necessary, and provide long-term monitoring. They may also coordinate pain management with oncologists and other specialists.
- Interaction with their oncologist (during consultations and when admitted to the hospital): Patients report their pain symptoms, discuss the effectiveness of their current pain management plan, and express concerns about side effects of medications. Oncologists evaluate pain intensity, determine its potential causes, and adjust analgesic treatment accordingly. When admitted to the hospital, pain is continuously monitored, and treatment plans may be modified based on the patient's evolving condition.
- Interaction with the nurse practisioner (during the nurse practisioner consultation hours): Nurse practitioners may conduct structured pain assessments and provide guidance on pain management strategies. They may adjust or initiate pain medications under supervision, educate patients on coping mechanisms, and discuss non-pharmacological pain relief options.
- Interaction with the nurses (when admitted to the hospital): Nurses perform regular pain assessments using validated scales and monitor the patient's response to pain treatments. They administer prescribed analgesics, document pain levels, and relay concerns to the oncology team. Nurses provide emotional support and assist with non-pharmacological pain management, such as positioning, relaxation techniques, or ice/heat therapy.

The interactions the oncologists could have regarding the pain assessment and management of one of their patients could involve:

- Interaction with the patient: Oncologists assess the patient's pain intensity, quality, and impact on daily life. They discuss pain management options, including medication adjustments, palliative care, and interventional procedures. They monitor treatment efficacy and make decisions about escalating or de-escalating pain relief measures.
- Interaction with the patients‖ important others: Oncologists may communicate with family members or caregivers to understand how the patient's pain is affecting their daily life. They provide guidance on supporting the patient's pain management at home and address concerns about treatment side effects or disease progression.
- Interactions with the general practitioner: The GP may refer the patient for specialist pain management or seek advice on adjusting medications. Oncologists may update the GP on treatment plans, especially in outpatient settings where the GP continues supportive care.
- Interaction with their co-oncologists: Oncologists may discuss complex cases with their colleagues to determine the best pain management strategy. They may collaborate on adjusting treatment plans based on tumor progression, side effects, or emerging evidence.
- Interactions with colleagues from other specialties: Pain management often requires input from anesthesiologists, palliative care specialists, neurologists, or physiotherapists. Oncologists may consult with these specialists for advanced pain control measures, including nerve blocks, spinal analgesia, or non-opioid strategies.
- Interactions with nurses: Nurses provide oncologists with regular updates on patients' pain levels, medication responses, and any concerns about worsening symptoms. They may suggest changes to the pain management plan based on observed patient needs.
- Interactions with documentation and research: Oncologists document pain assessments and treatment decisions in the electronic medical record (EMR), ensuring continuity of care. They may participate in pain-related research, contribute to clinical guidelines, or review scientific literature to improve pain assessment and treatment protocols.

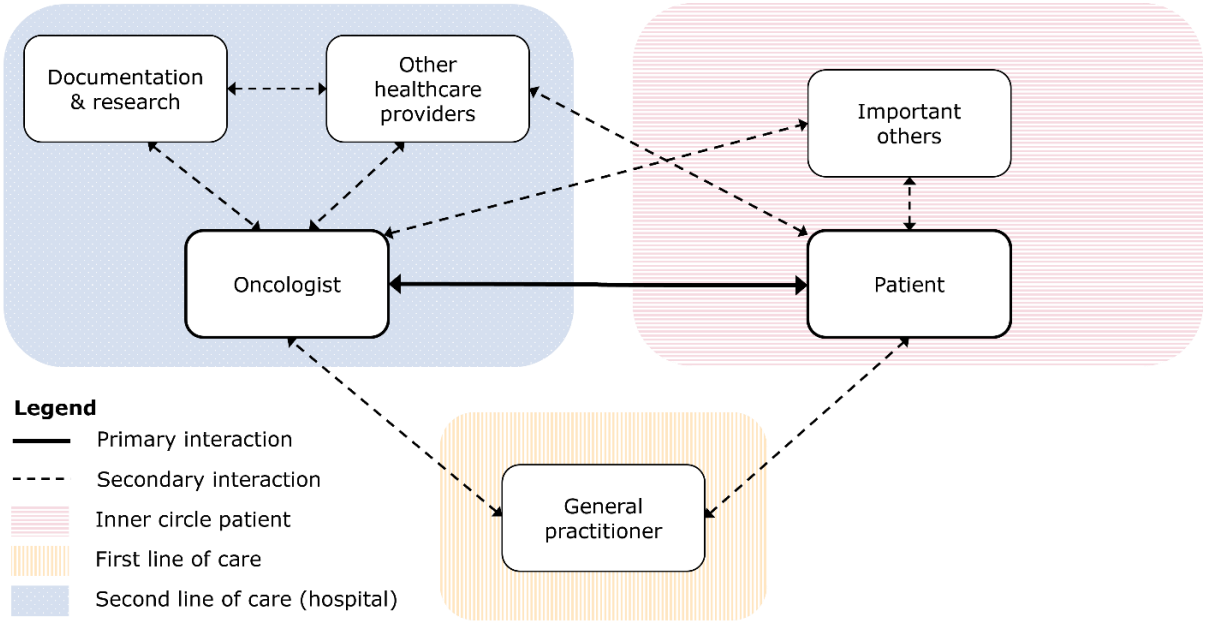


Figure 32 - Systematic mapping of the interactions patients and oncologists have regarding pain assessment, derived from the interviews with oncologists. The most important interaction is the interaction between the oncologist and the patient. All other interactions are secondary (dotted lines). The patient is closely related to the people within the patients' inner circle (pink circle). The patient has the option to interact with the first line of care (yellow circle), being the general practitioner, and the second line of care (blue circle), being healthcare providers in the hospital. The oncologist could interact with the same persons but could in addition to this also interact with the digital systems for documentation and research.

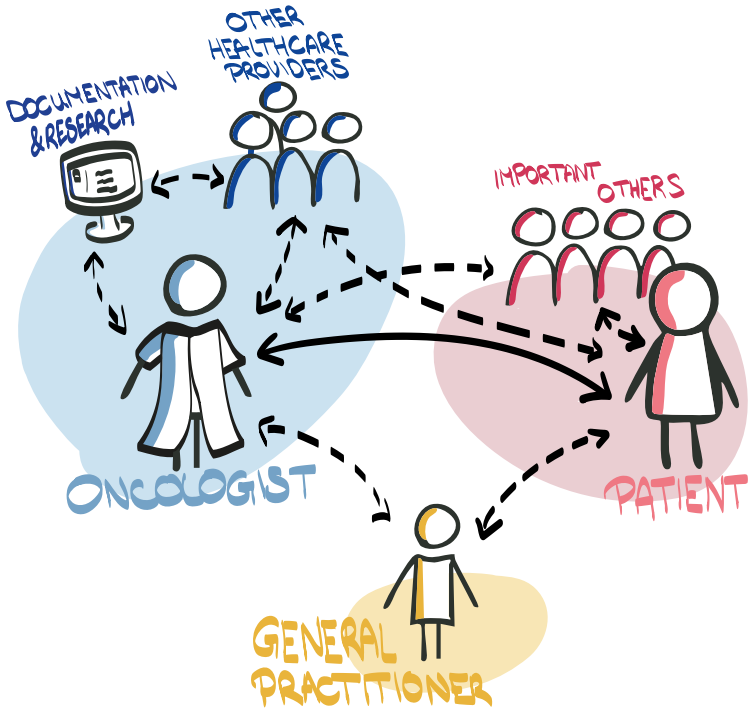


Figure 31 - Illustrative mapping of the interactions patients and oncologists have regarding pain assessment, derived from the interviews with oncologists. The most important interaction is the interaction between the oncologist and the patient. All other interactions are secondary (dotted lines). The patient is closely related to the people within the patients' inner circle (pink circle). The patient has the option to interact with the first line of care (yellow circle), being the general practitioner, and the second line of care (blue circle), being healthcare providers in the hospital. The oncologist could interact with the same persons but could in addition to this also interact with the digital systems for documentation and research.

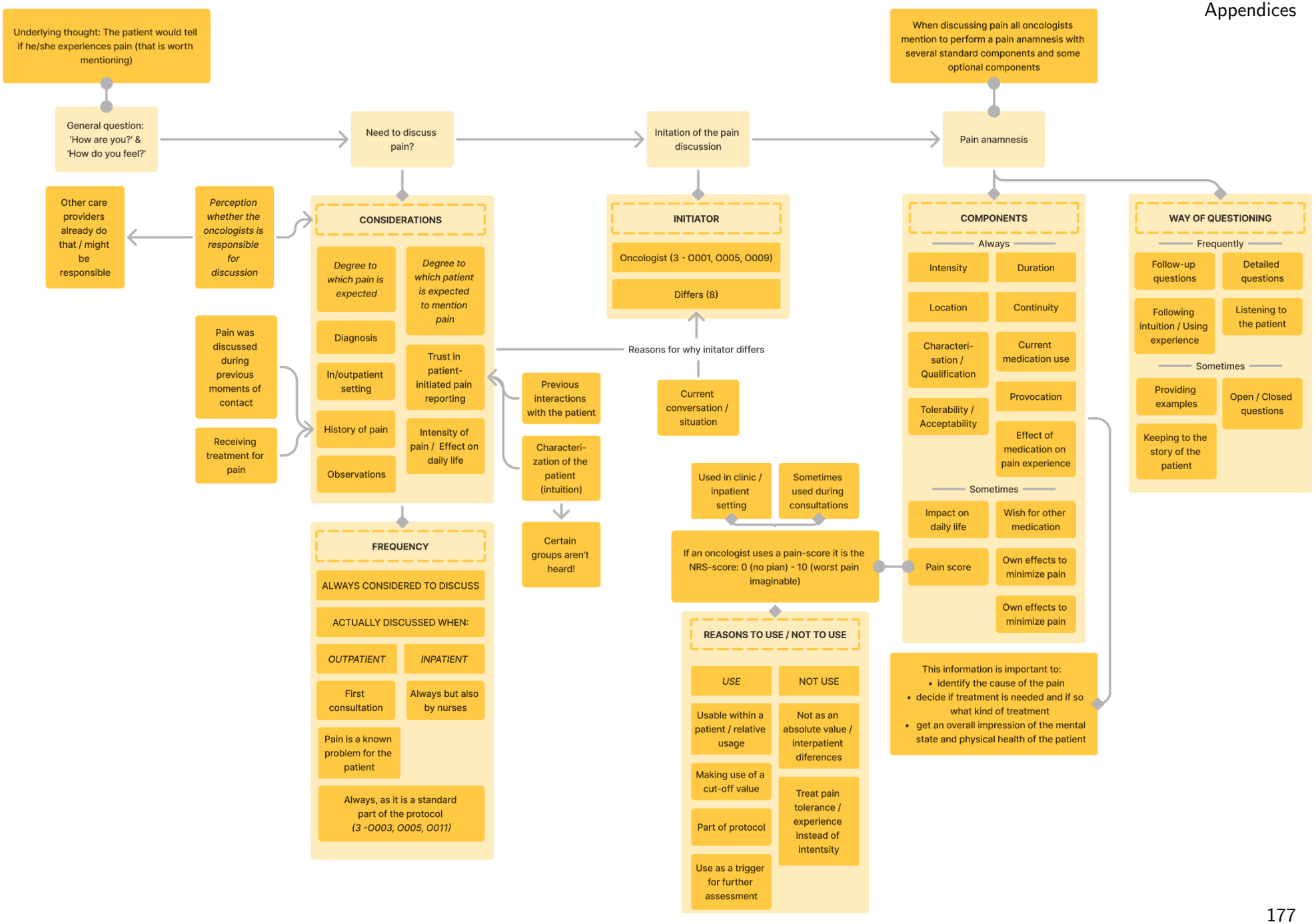
F.2 Process Mapping

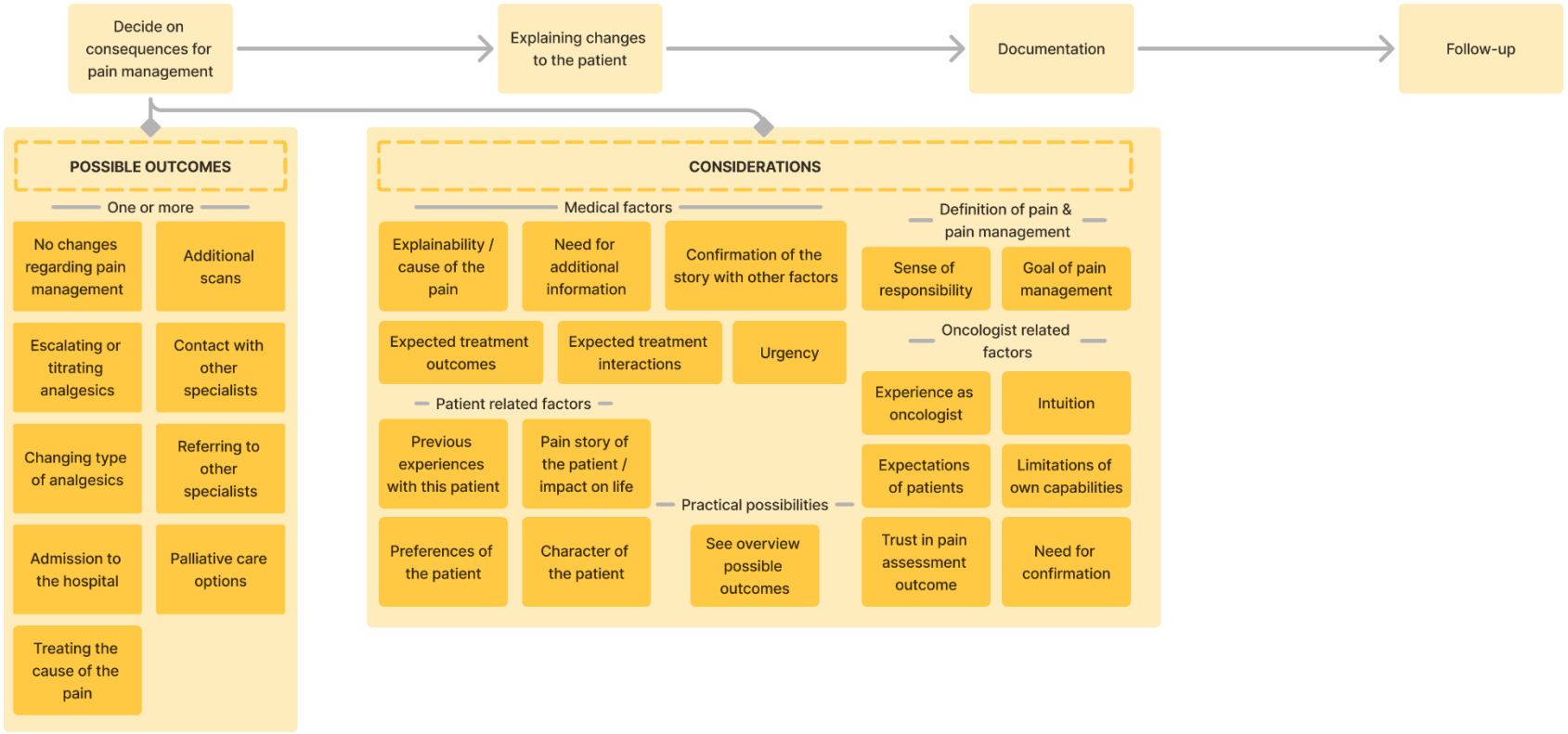
Although the pain assessment and management process varied depending on the context, several key stages that oncologists consistently followed could be identified from the interviews. The seven key stages are:

1) Identifying the need to discuss pain
2) Initiating the pain conversation
3) Conducting the pain anamnesis
4) Decision-making on the pain management actions
5) Communicating the pain management decisions to the patient
6) Documenting the assessment and treatment decisions
7) Follow-up and monitoring pain management

The process varies depending on the oncologists' preferences and routines, as well as logistical factors and the patient's individual circumstances, these key stages form the backbone of the current pain assessment approach used in oncological practice.

Originally all stages and the considerations associated with those stages were mapped as one flow in Figma, see the maps on the next two pages.


Underlying thought: The patient would tell if he/she experiences pain (that is worth mentioning)
General question: 'How are you?' & 'How do you feel?'
Need to discuss pain?
Initation of the pain discussion
When discussing pain all oncologists mention to perform a pain anamnesis with several standard components and some optional components
Pain anamnesis
Other care providers already do that / might be responsible
Perception whether the oncologists is responsible for discussion
CONSIDERATIONS
Degree to which pain is expected
Degree to which patient is expected to mention pain
Diagnosis
In/outpatient setting
Trust in patient-initiated pain reporting
History of pain
Intensity of pain / Effect on daily life
Observations
Pain was discussed during previous moments of contact
Receiving treatment for pain
Previous interactions with the patient
Characteri-zation of the patient (intuition)
Certain groups aren't heard!
Reasons for why initator differs
Current conversation / situation
INITIATOR
Oncologist (3 - 0001, 0005, 0009)
Differs (8)
FREQUENCY
ALWAYS CONSIDERED TO DISCUSS
ACTUALLY DISCUSSED WHEN:
OUTPATIENT
INPATIENT
First consultation
Always but also by nurses
Pain is a known problem for the patient
Always, as it is a standard part of the protocol (3 -0003, 0005, 0011)
COMPONENTS
Always
Intensity
Duration
Location
Continuity
Characteri-sation / Qualification
Current medication use
Provocation
Tolerability / Acceptability
Effect of medication on pain experience
Sometimes
Impact on daily life
Wish for other medication
Pain score
Own effects to minimize pain
Own effects to minimize pain
WAY OF QUESTIONING
Frequently
Follow-up questions
Detailed questions
Following intuition / Using experience
Listening to the patient
Sometimes
Providing examples
Open / Closed questions
Keeping to the story of the patient
Used in clinic / inpatient setting
Sometimes used during consultations
If an oncologist uses a pain-score it is the NRS-score: 0 (no pian) - 10 (worst pain imaginable)
REASONS TO USE / NOT TO USE
USE
NOT USE
Usable within a patient / relative usage
Not as an absolute value / interpatient diferences
Making use of a cut-off value
Treat pain tolerance / experience instead of intentsity
Part of protocol
Use as a trigger for further assessment
This information is important to:
• identify the cause of the pain
• decide if treatment is needed and if so what kind of treatment
• get an overall impression of the mental state and physical health of the patient


Decide on consequences for pain management
Explaining changes to the patient
Documentation
Follow-up
POSSIBLE OUTCOMES
One or more
No changes regarding pain management
Additional scans
Escalating or titrating analgesics
Contact with other specialists
Changing type of analgesics
Referring to other specialists
Admission to the hospital
Palliative care options
Treating the cause of the pain
CONSIDERATIONS
Medical factors
Explainability / cause of the pain
Need for additional information
Confirmation of the story with other factors
Expected treatment outcomes
Expected treatment interactions
Urgency
Patient related factors
Previous experiences with this patient
Pain story of the patient / impact on life
Preferences of the patient
Character of the patient
Practical possibilities
See overview possible outcomes
Definition of pain & pain management
Sense of responsibility
Goal of pain management
Oncologist related factors
Experience as oncologist
Intuition
Expectations of patients
Limitations of own capabilities
Trust in pain assessment outcome
Need for confirmation

G Themes Related to Reported Areas for Improvement

Oncologists identified several areas for improvement in pain assessment and management, highlighting the need for more structured monitoring, better communication, and the integration of supportive tools. Many of the suggested improvements focused on increasing the continuity and objectivity of pain assessment while ensuring that patients have clearer guidance on when and how to report pain.

A major theme across the suggestions was the need for better pain monitoring, particularly in the outpatient setting. Oncologists expressed a desire for more frequent pain assessments between consultations to track trends over time rather than relying solely on isolated reports during appointments. Some suggested structured self-monitoring by patients, where patients could regularly document their pain levels, experiences, and medication use outside of consultations. Others proposed the use of digital tools such as apps to facilitate pain tracking and automatic uploads of patient-reported pain data into electronic medical records. This could help oncologists detect deteriorations earlier and tailor consultations more effectively:

"If we could have more insight into how pain develops between consultations, we'd know much better where to start the conversation." – O05

Additionally, oncologists highlighted the need for more objective pain assessment methods to complement subjective patient reports. Suggestions included tracking medication usage, incorporating physiological measures, and considering activity levels and sleep patterns to gain a more comprehensive view of the patient's pain experience. Some oncologists saw potential in non-verbal pain assessment tools, which could use facial expressions, voice patterns, or movement analysis to aid in pain evaluation.

"In essence, I think we are all looking for more objective measures to truly objectify their pain experience." – O08

Another frequently mentioned improvement was enhancing communication and information flow. Oncologists suggested better pre-consultation pain reporting, where patients could provide structured information on their pain in a quiet environment before their appointment. This could help oncologists determine the consultation's focus and ensure that pain discussions are not overlooked due to time constraints. Furthermore, they proposed standardising pain assessment approaches across healthcare professionals to reduce inconsistencies, particularly in indirect pain assessments from nurses or caregivers.

"For example, you would want there to be a dedicated patient page in HIX, properly set up for patients, without giving them access to the entire HIX system. Where you could say, 'This is your

file, please fill in how you have experienced the past two weeks. Did you have pain? Perhaps include a pain score. Where was the pain located?' And then, before I call in Mrs. Jansen, I could already see, 'Okay, this patient has a pain score of 1 and is satisfied, so I can wrap this up quickly.' But if someone reports a score of 8 or 9 or higher, I know, 'Okay, I really need to focus on this during the consultation because something is going on." – O08

Some oncologists also advocated for stronger collaboration between specialties and better integration of pain information into shared medical records. Contact with general practitioners was identified as a potential way to improve long-term pain monitoring, ensuring that pain discussions continue beyond oncology appointments.

"I definitely think that [...] there are still improvements to be made within this hospital, as well as in better collaboration with the pain team, because that was quite limited in our hospital." – O05

Beyond structural changes, oncologists emphasised the importance of education on pain assessment and management, both for healthcare professionals and patients. They saw room for improvement in helping patients understand their pain, medication use, and self-management strategies, which could empower them to take a more proactive role in reporting and managing pain.

"I think that if you only look at what would be best, then I believe that patients should be given much more control." – O09

Overall, these suggestions reflect a shared goal: making pain assessment more continuous, objective, and integrated into routine care while ensuring that patients receive the necessary support to communicate their pain effectively.

H Themes Related to Design and Implementation Preferences

Quotes relevant to the design and implementation preferences are presented in Table H.1.

H.1 Accessibility

Oncologists emphasized that the tool must be easy to use, quick to access, and seamlessly integrated into existing workflows. A frequently mentioned concern was the burden on both patients and clinicians, with oncologists stressing that the tool should require minimal effort from users. Some suggested that patients should not have to log in manually but instead use automatic authentication methods or a direct link from the patient's EMR. Additionally, they highlighted the importance of multilingual support to ensure accessibility for a diverse patient population. For oncologists, accessibility also meant that pain assessment results should be readily available within existing hospital systems. Several oncologists preferred integration with HIX, the standard EHR system, to avoid using a separate platform. In the early stages, when the tool would be used for research purposes, they generally mentioned to allow other methods to access the tool outcomes, such as a web-based interface.

H.2 Graphical Representation of Data

A key theme was the importance of clear and intuitive data visualisation. Oncologists preferred graphical representations over raw numerical outputs, as trends over time provide more actionable insights. They suggested that pain trajectories should be displayed in a way that allows for at-a-glance interpretation, similar to how lab values are presented in clinical practice. Additionally, oncologists expressed interest in overlaying pain trends with other relevant data, such as medication use, sleep patterns, and daily activity levels. This would help them assess how different factors influence pain and provide more comprehensive patient management. Some also mentioned that comparative data (e.g., average pain scores across similar patients) could aid interpretation, though they stressed that this should not replace individualized assessments.

H.3 Notification Preferences

While oncologists acknowledged the potential benefits of receiving alerts for concerning pain trends, they strongly emphasized that notifications should not be excessive or disrupt their workflow. Several oncologists expressed concern about receiving too many unnecessary alerts, which could lead to alarm fatigue. Instead, they preferred customizable notification settings, allowing them to define when and how they receive alerts.

Most oncologists suggested that alerts should only be triggered when pain trends indicate a significant clinical concern, such as a sudden increase in pain or worsening symptoms over time.

Some proposed that alerts should be handled through a triage system, where a nurse or designated team member filters notifications before they reach oncologists.

H.4 Capturing Contextual Information

Oncologists emphasized that pain scores alone are insufficient for meaningful clinical decision-making and that contextual information should be recorded alongside the AI-generated assessments. They suggested several additional data points that could enhance interpretation, including:

- The relationship between pain and medication use (e.g., whether pain improves after taking analgesics).
- Daily activities and functional status to assess how pain impacts daily life.
- Other symptoms such as fatigue, nausea, or psychological distress.
- A brief note from the patient to provide qualitative context about their pain experience.

Table H.1 Quotes relevant to Behavioural Intention

Subtheme	*Relevant Quotes*
Accessibility	"I think you want to integrate as much as possible into one system, one, let's say, mother system, and that you want to create as many connections as possible to that mother system. Whether it's an EHR or other branches, as long as they are connected to each other. This way, you don't have to enter data in multiple places, but data can be automatically transferred from one place to another without requiring manual input, as the system would handle it itself." – O02 "I think having multiple language options is just something that needs to be considered." – O08
Graphical representation	"Graphical representation is always the best because it allows you to see at a glance what is going on. It would be ideal if you also had the option to click through for more details if needed, but I think having a quick visual overview that instantly tells you, 'Do I need to act on this? Yes or no?' works best. It's better than having to read through text first to determine whether action is needed." – O09 "It seems logical that you would present it in a graph over a certain period or provide an average, maybe even an average of the overall population." – O04
Notification preferences	"What you could develop, perhaps, is some kind of alarm system. If consistently high scores are reported, an automatic appointment could be scheduled at the outpatient clinic, or a notification could be sent to the nurse, who could then discuss it with you. That would be a great feature." – O07
Contextual information	"I think you should also include pain medication usage in the application. There should be an overview of what the patient is actually using, when they have taken short-acting opioids, and what effect it had. If you really want to do it well, you would also track side effects. But then, of course, it becomes a much more intensively used tool."- O09 "We always try to assess how fit a patient is, but patients often present themselves as being in better condition than they actually are. So maybe that could also be measured?" – O11 "You might also want to include an additional note alongside the data."" – O02
Providing clinical advice	"And perhaps the model could be trained intelligently enough to provide instructions to the patient based on the assessment." – O11

One oncologist highlighted that pain perception is subjective and influenced by multiple factors, and thus, the tool should capture not only pain intensity but also its impact on the patient's quality of life. Others suggested that the system should allow for trend analysis over longer periods, helping oncologists differentiate between acute pain episodes and chronic worsening.

H.5 Providing Clinical Advice

For patients, oncologists envisioned that the tool could provide automated guidance on managing pain. This feature could empower patients by providing personalized advice on coping with pain while also reducing reliance on oncologists for every minor pain fluctuation.

I Expert Consultations

I.1 A.1 Temitayo Olugbade

Dr. Temitayo Olugbade, an applied AI researcher at University College London, provided insights into affective computing and the role of machine learning in modelling human psychological states. Her expertise helped refine how the AI-based APA tool could analyse pain-related facial and vocal expressions for improved pain assessment.

I.2 A.2 Nadia Berthouze

Professor Nadia Berthouze, a leading expert in affective computing at UCL, advised on leveraging body movement and sensory feedback in AI-driven pain assessment. Her input contributed to shaping the tool's approach to recognising subtle affective cues in facial expressions and voice for more accurate pain evaluation.

I.3 A.3 Deborah Forster

Dr. Deborah Forster, a transdisciplinary researcher at TU Delft, provided expertise in human-robot interaction and cognitive science, particularly in understanding expert sense-making. Her consultation helped ensure that the tool's AI-driven assessments align with real-world clinical decision-making processes.

I.4 A.4 Socially Perceptive Computing Lab

The Socially Perceptive Computing Lab at TU Delft contributed expertise in multisensor fusion, particularly in synchronising audio and visual data. Their input was instrumental in designing data collection methodologies that enhance the AI model's ability to interpret pain-related nonverbal cues.

I.5 A.5 Intelligent Sight & Sound Research Group

The Intelligent Sight & Sound Research Group, based in Washington, provided insights from their experience in developing similar AI-driven pain assessment databases. Discussions focused on potential collaboration opportunities and best practices for structuring and validating the APA tool's dataset.

J Brainstorm Preparation

For the brainstorm session with the research group, a Figma board was prepared to structure the session. Figure 33, Figure 34, and Figure 35 present the digital preparations.

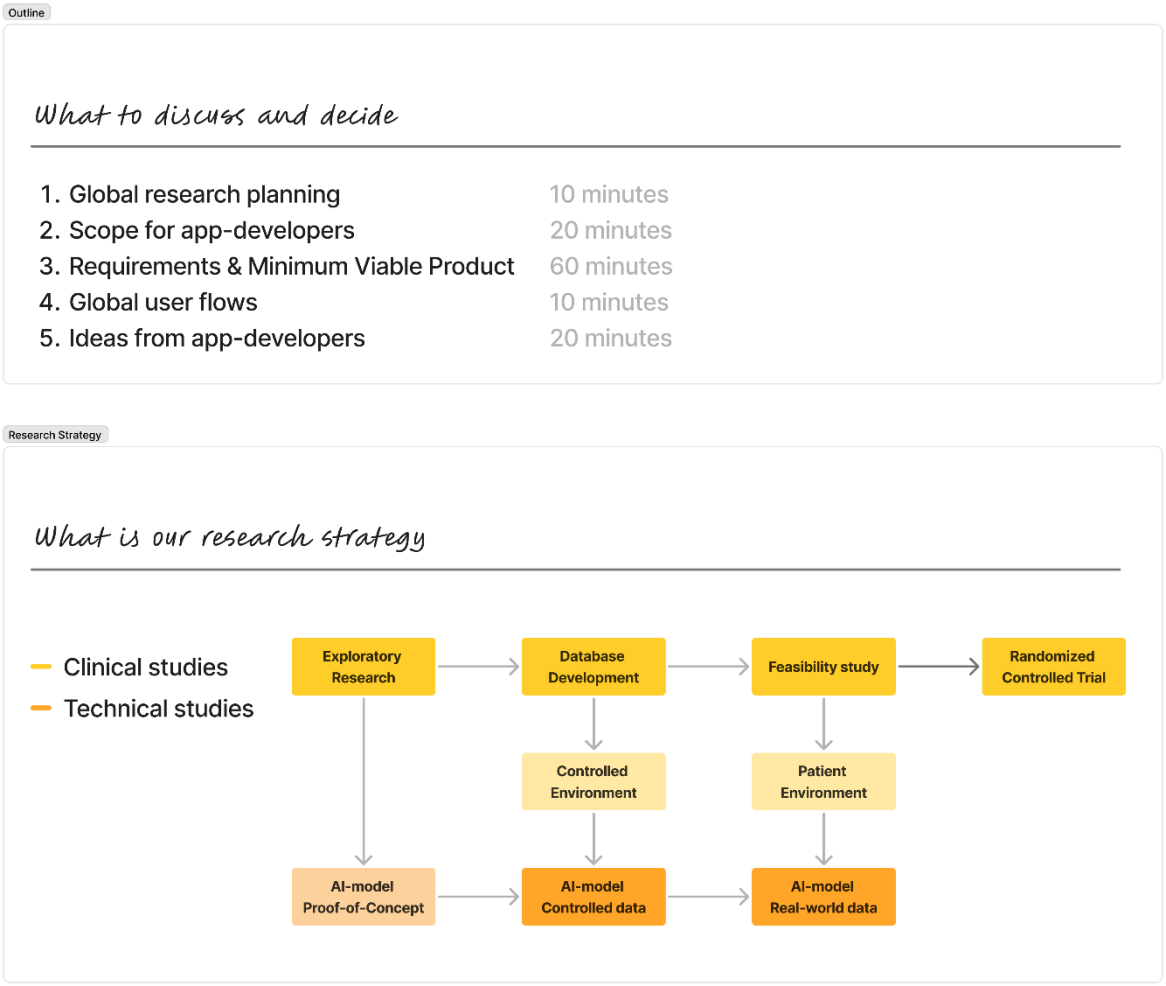


Figure 33 - Session outline and assumed research strategy for the SENSAI-project

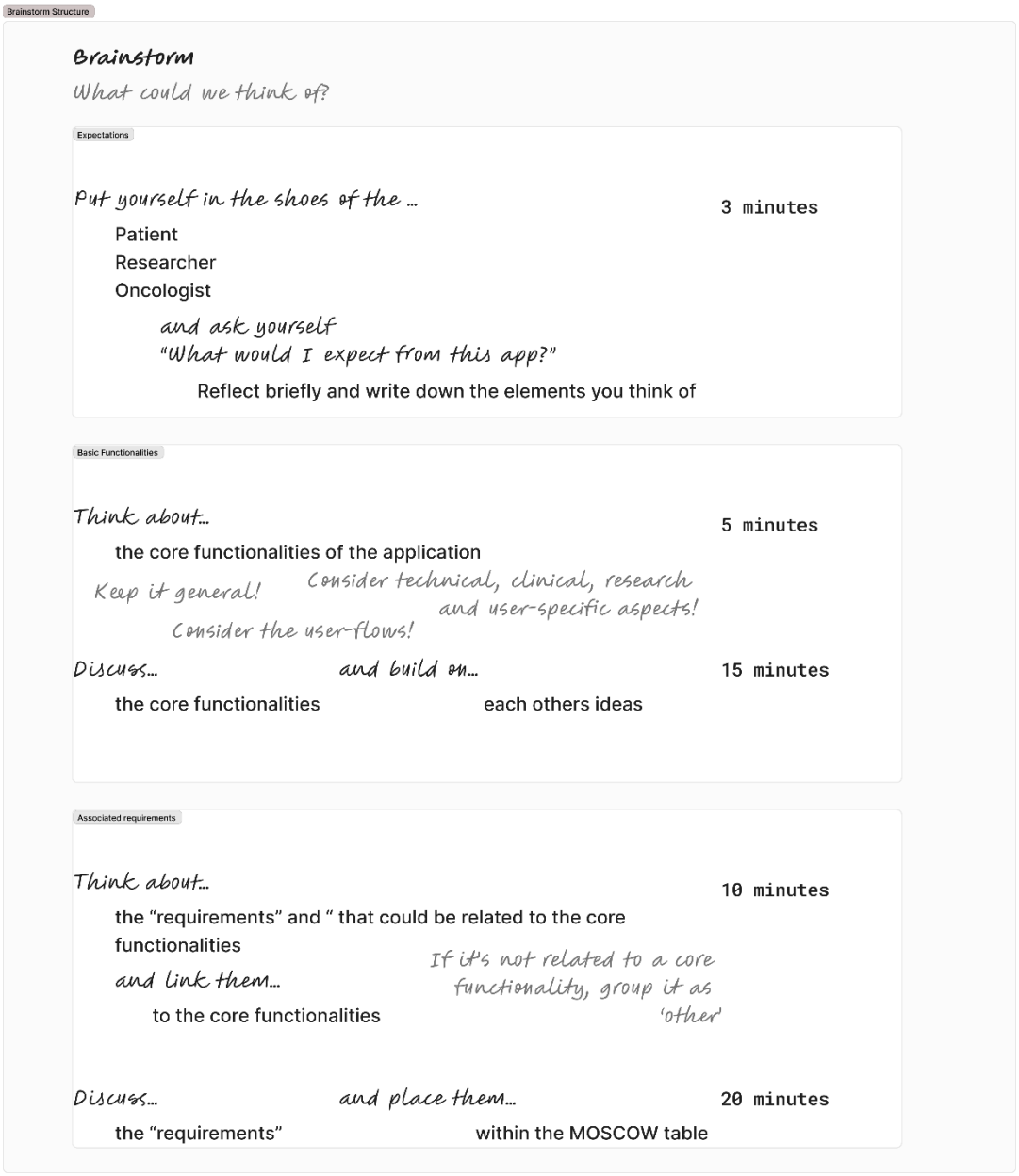


Figure 34 - Outline of the brainstorm part of the session with the goal of identifying functionalities and requirements

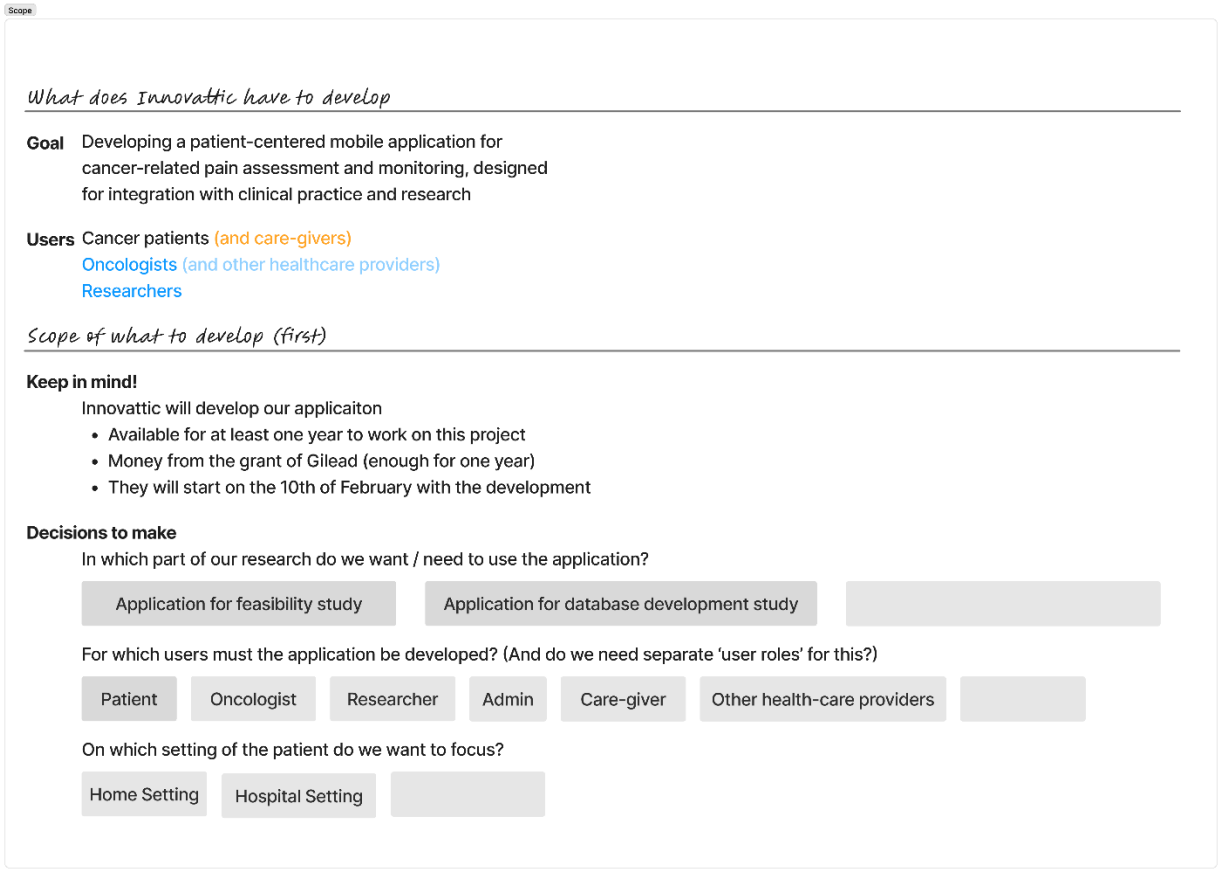


Figure 35 - Prepared summary for the outcomes of the session

K Brainstorm Outcomes

During the brainstorm sessions several ideas were presented. First a thought exercise was done on the expectations the end user could have of the tool. Figure 36 presents the outcomes. Later in the brainstorm session ideas were generated for the functionalities of the tool. Figure 37 presents a snapshot of some of the outcomes.

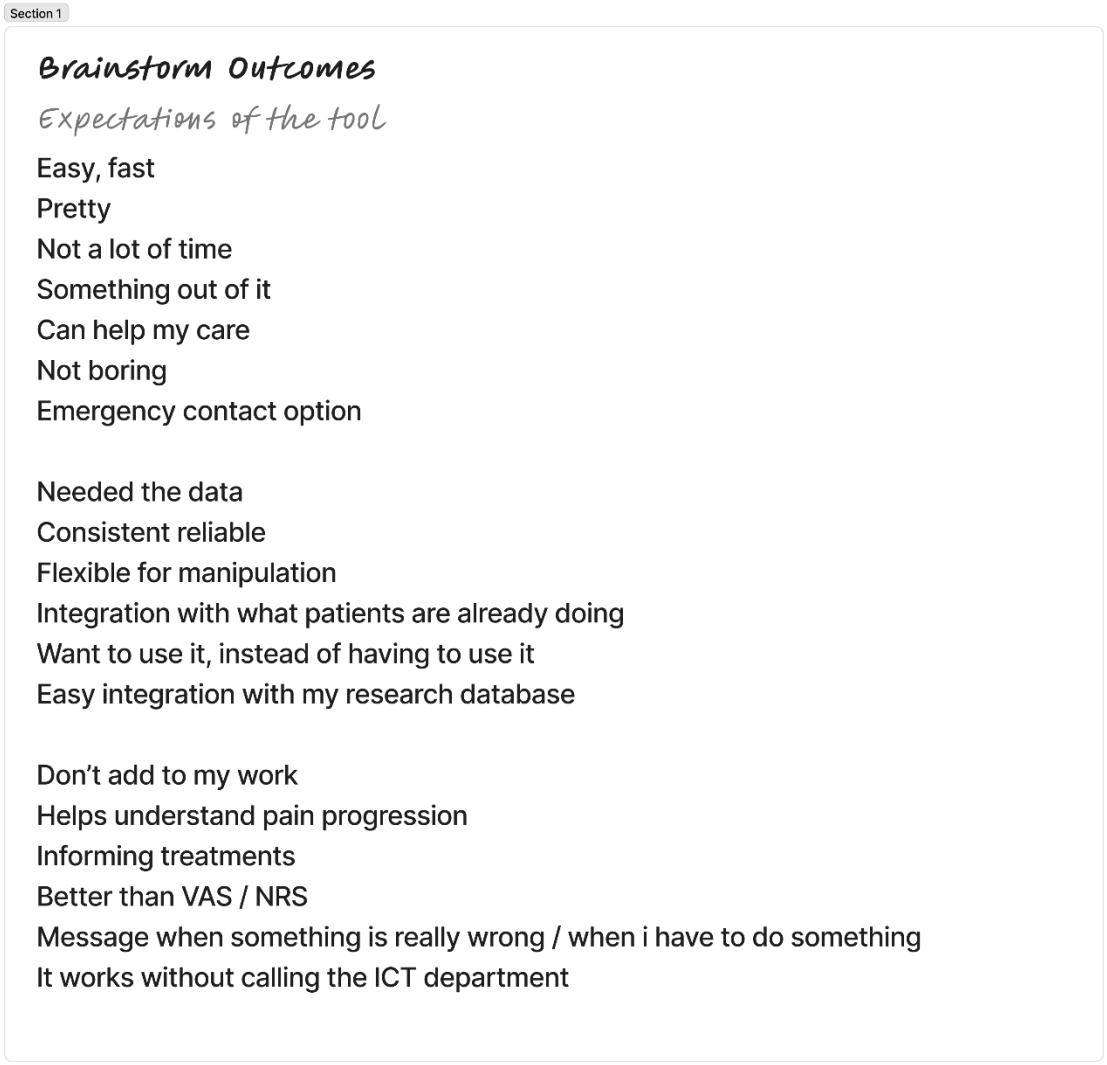


Figure 36 - Brainstorm outcomes - Perceived expectations of the end-users of the tool

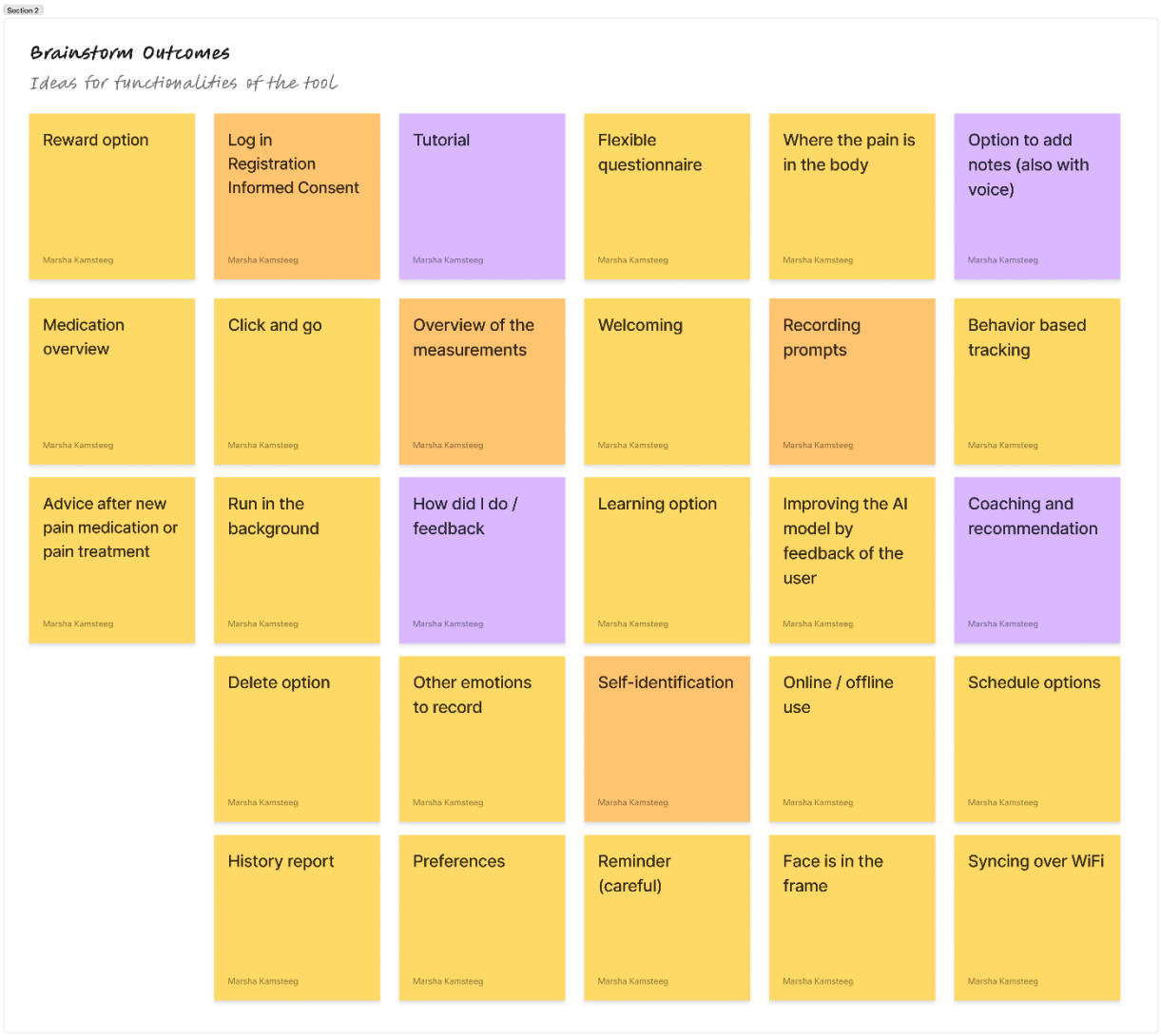


Figure 37 - Brainstorm outcomes - Ideas for the functionalities the tool might have. Orange indicates main functionalities, yellow indicates secondary functionalities, purple indicates functionalities that might help the patient

L MoSCoW Overview Patient Application

Figure 39 and Figure 38 show the MoSCoW-requirement overviews for the researcher application (built in sprint 1) and for the patient application (started with the development in sprint 2), respectively.

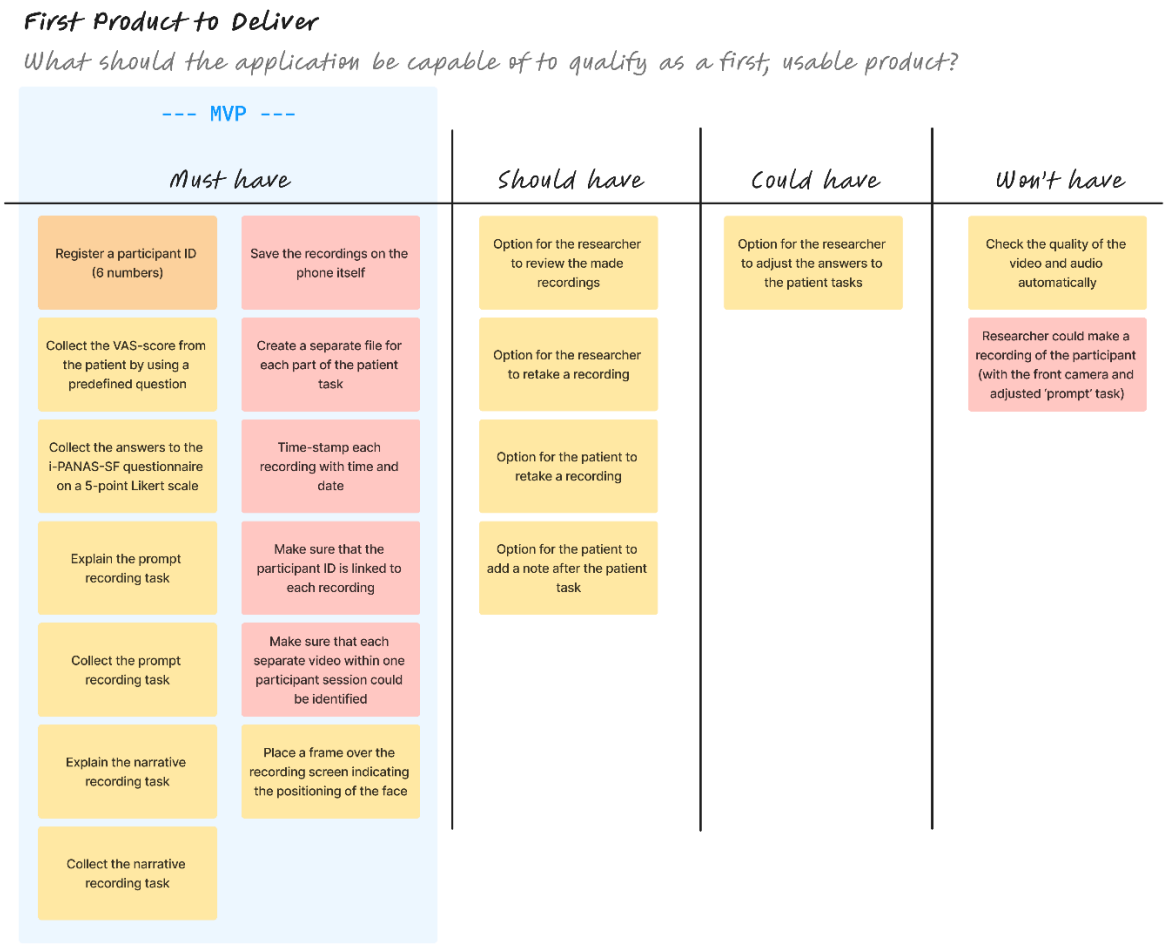


Figure 38 - MoSCoW requirements overview for the researcher application

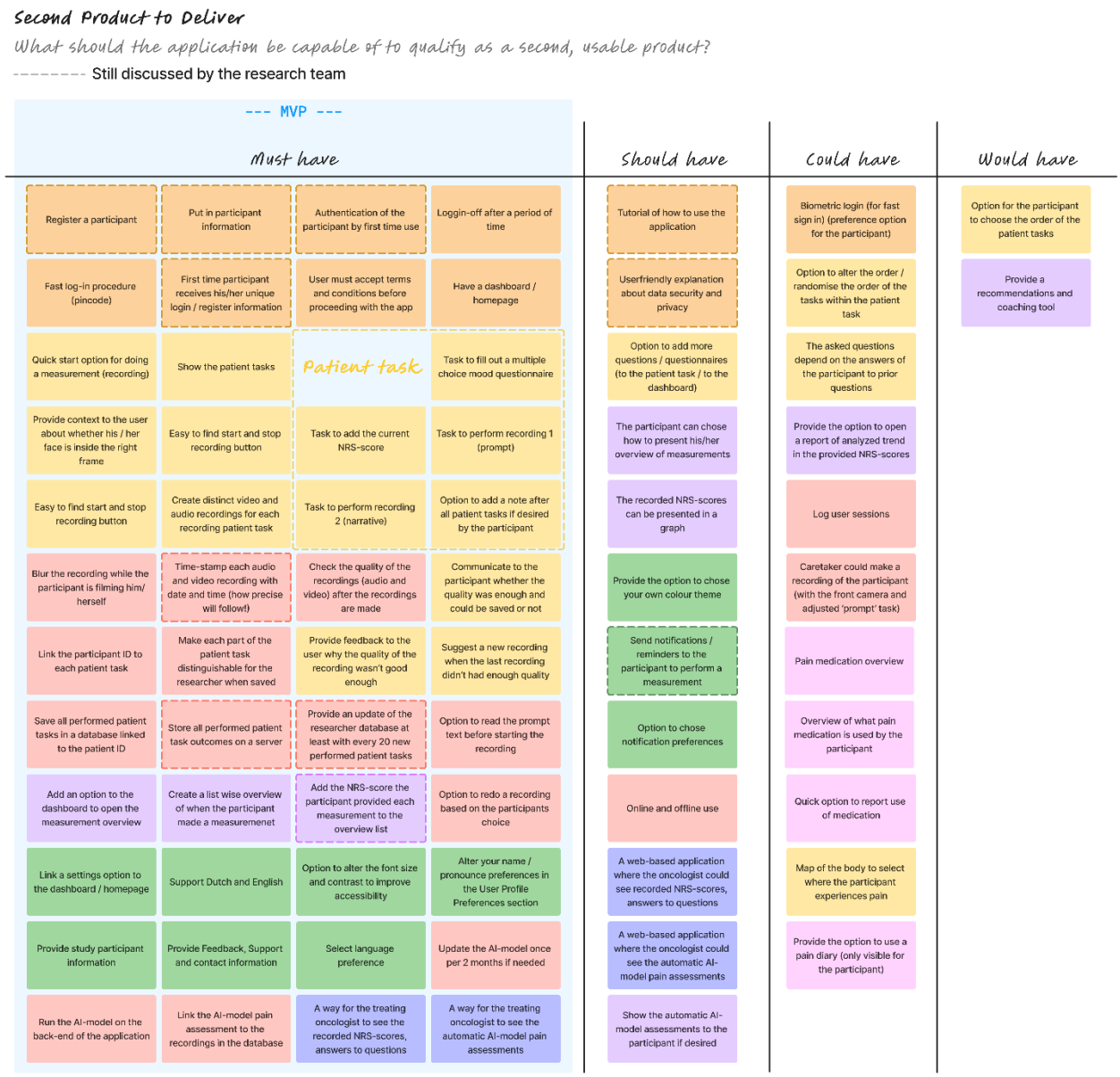


Figure 39 - MoSCoW Requirements Overview for the patient application [under development]

M Setup Considerations and Requirements

Designing a flexible and standardised recording setup is essential to ensure consistent data collection while accommodating variations in the clinical environment. The setup must adapt to different patient rooms, technical constraints, and hospital protocols while maintaining patient comfort and data quality and be within budget.

M.1 Adapting to Different Patient Rooms and Conditions

Patient rooms vary in size, layout, lighting, background elements, and noise levels from medical equipment such as medicine pumps. The setup must accommodate these differences to ensure clear audiovisual recordings. Patients may be in different positions within the room, but they will be asked to sit upright in bed whenever possible to maintain a standardised recording angle. However, comfort and mobility limitations must be considered.

M.2 Technical Constraints and Equipment Placement

The recording equipment must function in rooms with varying power socket locations, available space, and background objects. A movable hospital table will be used to position the setup, allowing flexibility while keeping the equipment close to the patient. This approach also ensures transportability between rooms and compliance with hospital infection control and safety protocols.

M.3 Audio and Visual Standardisation

Variations in lighting, noise levels, and patient speech characteristics must be addressed to ensure high-quality recordings. While background conditions cannot be fully controlled, efforts will be made to achieve a neutral recording environment. The setup will minimise occlusion risks and inconsistent framing while adapting to differences in patient height, posture, and skin tone.

M.4 Smartphone as a Secondary Recording Device

A smartphone will be integrated as a secondary video and audio recorder to evaluate whether its data quality is sufficient for AI-based pain assessment. Since the envisioned clinical application involves patients recording themselves via a smartphone app, the phone will be positioned to simulate a natural selfie recording while avoiding interference with the primary high-end camera.

M.5 Special Considerations for Patients in Isolation

For patients in infection-controlled isolation, adjustments may be needed to maintain safety and comply with hospital protocols. This could include using disinfectable covers or modifying the setup to avoid direct handling of equipment.

By addressing these factors, the study ensures a consistent, adaptable, and patient-friendly recording setup while maintaining high data quality and clinical feasibility.

M.6 Feasibility

For the recording setup to be viable within the study, it must be cost-effective, practical to assemble, and require minimal effort for implementation.

M.7 Requirements

In Table M.1 an overview could be found of the defined requirements and wishes related to the setup used for the database development study.

Table M.1 Requirements overview related to the setup

Specification	Requirement	MoSCoW
Camera positioning	The camera must be placed at a fixed position with a clear, unobstructed view of the patient's face.	Must
	The camera must capture the frontal 90 degrees of the face.	Must
	The camera should be at eye level with the patient to ensure the best capture of facial expressions. *When the camera is positioned at eye level, the whole face and the expressions will be captured in the best possible way. However, databases like the UNBC use a slightly different angle (-30°, from below).*	Should
	The camera must capture the whole face of the patient, no subjects in the background and minimal irrelevant background objects.	Must
	The background should be plain to minimise noise for the algorithm	Should
	No zooming function should be needed to capture the whole face without capturing additional background space.	Should
	The camera must be placed in front of the patient at a distance that allows the camera to capture the whole face. *The exact distance depends on the camera specs (Field of View, resolution)* *Pain databases do not explicitly describe the distance used.*	Must
	The camera must be positioned on a stable surface to avoid movement during recording. *This ensures consistent positioning across recordings and reduces the risk of shaky footage. This could be done with a tripod or through mounting the camera to the wall/ceiling/bed.*	Must
	The camera setup should have an adjustable height and tilt, to allow for fine-tuning the camera angle, maintaining eye-level positioning with different patients and adjusting for differences in the patient rooms.	Should
	If chosen for a synchronisation method using the hardware itself, the camera must be physically connected to the high quality microphone to be able to ensure synchronisation.	Must

Audio mounting	The microphone must be positioned at a distance that captures the patient's voice clearly without distortion. *The exact distance depends on the microphone specs (type, sensitivity, directivity etc.)*. Typically it would be 20-30 cm from the mouth.	Must
	The microphone must be directed towards the patient's voice to minimise background noise.	Must
	The microphone should be mounted securely in a fixed position to avoid any movement during recording, ensuring consistent audio quality.	Must
	The microphone should be mounted in an adjustable holder or arm that allows easy repositioning without requiring complex disassembly or adjustment.	Should
	Flexible arms or adjustable clips could be used to allow positioning the mic easily.	Could
	The mounting system should be adaptable to different room layouts and sizes, whether it's attached to the bed, a nearby table, or the ceiling.	Must
	The microphone should not be placed too close to any sources of potential noise (e.g., ventilators, pumps), as this could degrade the quality of the recording.	Should
	The microphone should be placed near equipment that might produce electromagnetic interference (such as medical devices like pumps, which may cause audio distortion).	Should
	If chosen for a synchronisation method using the hardware itself, the microphone must be physically connected to the high quality camera to be able to ensure synchronisation.	Must
Smartphone placement	The mobile phone must not be placed in sight of the high-end camera.	Must
	The selfie / front camera must be directed to the patient's face.	Must
	If a less realistic clinical application scenario, but a more high quality smartphone recording is desired for the smartphone recording the following requirements apply:	
	The mobile phone must be in a fixed position relative to the patient, ensuring that it captures the required facial expressions without moving throughout the recording.	Must
	This could be achieved by mounting it on a tripod, phone stand, or a stable surface.	Could
	Once set up, the mobile phone should not require frequent adjustments in angle or distance to maintain consistency across sessions.	Should
	If a realistic clinical application scenario is desired for the smartphone recording the following requirements apply:	
	The phone should be placed at a maximum of arm length (max 1 metre).	Should
	The phone should be pointed at the patients' face, while the patient is flexing his/her head within a range of -45° and +10° (where facing downwards is considered negative) [1]	Should
Setup placement	The complete setup must be easily repositioned and transported between patient rooms, maintaining similar positioning across rooms.	Must
	The setup must not obstruct access to medical equipment or interfere with clinical procedures.	Must
	The complete setup could be mounted to a portable / movable base / platform, ideal while using a fixed setup in different rooms while ensuring consistency across recordings.	Could

	If a power supply cable (or multiple power supply cables) are required for the setup equipment, the cables must be long enough to reach the power sockets from the equipment in their mounting position but short enough to avoid tangling or being in the patient's way. *It could be expected that a length of 3 metres would be enough to meet this requirement.*	Must
	The setup must be safe for hospital use, ensuring cables are managed to prevent tripping hazards.	Must
Positioning of the patient	The patient should not be required to make unnatural movements, as posture and comfort can impact their pain expression.	Could
	The patient must sit in order to be able to create a stable recording.	Must
	The patient should be sitting in the hospital bed to create similar backgrounds as much as possible.	Should
Appearance	The camera should be positioned in a way that doesn't intrude on the patient's personal space or cause discomfort. *The setup should be subtle to avoid affecting the patient's natural behaviour or facial expressions.*	Must
	The mounting system should be discreet, placing the microphone in a way that doesn't intrude the patient's personal space or cause discomfort.	Must
Environment	The lighting must be sufficient to ensure the patient's face is well-illuminated, avoiding underexposure or excessive shadows.	Must
	The setup must accommodate different hospital lighting conditions, including natural light, artificial overhead lighting, and bedside lamps.	Must
	The lighting must not create glare on the patient's skin, which could distort feature extraction in AI processing.	Must
	The researcher must ensure clear speech capture with minimal background noise, allowing accurate analysis of vocal characteristics.	Must
Other	The recording setup must be within the budget of €1000,-.	Must
	The recording setup should require no more than 3 hours of work for first implementation.	Must

N Equipment Requirements

In Table N.1 the requirements for the high-quality camera are presented, whereas in Table N.2 the requirements for the high-quality audio-recorder are presented.

Table N.1 Requirements overview for the high-quality camera

Specification	Requirement	MoSCoW
Resolution	The camera must at least have a resolution of 1080p (Full HD). UNBC database uses 640 x 480 pixels/frame BioVid database uses 1388 x 1038 pixels/frame BP4D database uses 1040 × 1392 pixels/frame EmoPain database uses 1024 x 1024 pixels/frame The most currently developed databases (Gutierrez et al. (2024)) use 4K 4096 x 2160 pixels/frame	Must
	The camera we use should have a 4K resolution for detailed analysis of facial expressions. 4K is increasingly preferred for detailed analysis of facial expressions.	Should
	The resolution won't have to be higher than 4K. Higher resolution is particularly useful for micro-expression detection, allowing algorithms to pick up subtle muscular movements and facial changes. But this might be out of scope for now and would probably only result in large files and longer computational times. There must be a trade-off.	Won't
Frame rate	The frame rate must be at least 25 frames per seconds (fps) to capture the dynamics of facial expressions. For affective computing tasks, a frame rate of 25 to 60 frames per second (fps) is typical to accurately capture the dynamics of facial expressions. UNBC database uses 30 fps BioVid database uses 25 fps BP4D database uses 25 fps EmoPain database uses 58 fps The most currently developed databases (Gutierrez et al. (2024)) use 90 fps	Must
	A frame rate of more than 60 fps won't be necessary. Higher frame rates like 120 fps may be used in specific cases for capturing fast, involuntary facial movements relevant in pain assessment.	Won't
Field of view	The field of view of the camera must at least be 60 degrees to capture the whole face of the patient from a frontal position (but depends on the distance between the camera and the face of the patient).	Must

	A typical FOV for facial analysis would be around 60 to 90 degrees. When the distance becomes larger between the patient and the camera a smaller field of view might probably suffice. The EmoPain database uses 90 degrees. The most currently developed databases (Gutierrez et al. (2024)) use up to 90 degrees.	
	The field of view of the camera should be up to 90 degrees in order to capture the whole face of the patient from a frontal position even when the patient would move during the recording.	Should
Synchronisation options	It must be able to synchronise the recordings from the camera with the recordings from the audio recorder. Synchronisation can be achieved through various methods and to varying degrees of precision, see below.	Must
	The camera must be able to time-stamp all recordings.	Must
	The camera must have an audio input, in order to be able to physically connect the audio recorder to the camera.	Must
	The camera could have a XLR-audio connection, since these cables are designed for balanced audio, reducing the amount of noise and interference over long distances and significantly reducing noise from electromagnetic fields.	Could
	It might be helpful to be able to synchronise the recordings from the camera and audio recorder with the mobile phone. This is not necessary, but might become practical in a later stage of the project when we might want to train the model on the data from all three devices.	Could
	The camera must have the ability to connect to ethernet / WiFi in order to synchronise with the mobile phone.	Must
Format	The camcorder must record in high-quality formats such as AVCHD, MP4, or MOV. These formats strike a balance between quality and file size, although uncompressed or less compressed formats like ProRes may provide better fidelity for analysis.	Must
Storage compatibility	The camcorder must use compatible storage media (like SD cards) that support the required speed class for the video resolution and frame rate to prevent dropped frames.	Must
Stabilisation features	It must be able to connect the camcorder to a stable setup, like a tripod, or the camcorder must have stabilisation features to ensure visual stability of the recording.	Must
Practical	The camcorder could be compact and lightweight in order to easily move it from patient room to patient room and store when not used.	Could
Appearance	The camcorder should appear discrete to minimise the feeling of being observed and altering the patient's natural behaviour.	Should
Costs	The camcorder won't cost more than €800,-.	Won't
	The camcorder must be as cheap as possible, while reaching the other requirements.	Must

Table N.2 Requirements overview for the high-quality camera

Specification	Requirement	MoSCoW
Resolution	The audio recorder must support at least 24-bit audio resolution at a rate of 48 kHz to ensure high-quality recordings that capture subtle vocal nuances effectively. EmoPain database uses 48 kHz 24 bit Pulse Code Modulation The most currently developed databases (Gutierrez et al. (2024)) use 16 bit 48kHz (the Rode NT-USB).	Must
	The audio recorder could ideally support higher sample rates (e.g., 96 kHz) for even better fidelity, particularly useful for research applications focused on emotional or pain-related vocal variations.	Could
Dynamic range	The audio recorder must have a wide dynamic range (at least 100 dB) to capture both soft and loud sounds without distortion, crucial for clear voice recording.	Must
Frequency range	The audio recorder must have a frequency response range of at least 20 Hz to 20 kHz to adequately capture the full spectrum of human speech, which typically falls within this range. The most currently developed databases (Gutierrez et al. (2024)) use a range of 20 Hz to 20kHz.	Must
	The field of view of the camera should be up to 90 degrees in order to capture the whole face of the patient from a frontal position even when the patient would move during the recording.	Should
Pickup pattern	The pickup pattern of the recorder should be narrow, so the type should be e.g., shotgun or cardioid, to ensure that sound is primarily recorded from the direction of the speaker, while rejecting sound from the sides and rear. The X-ITE database and Emopain database used directional microphones. (link) The most currently developed databases (Gutierrez et al. (2024)) use directional microphones (cardioid).	Should
Directivity	The audio recorder should effectively capture sounds in front of it and reduce surrounding noise.	Should
Connectivity	The audio recorder must have a connector that suits the audio connection option of the camcorder, in order to link the devices.	Must
Format	The audio recorder must support common formats like MP3, WAV or AIFF.	Must
	The audio recorder should support common formats like WAV or AIFF for uncompressed audio, ensuring high fidelity for analysis.	Should
Storage compatibility	The audio recorder must utilize SD cards or other flash storage media that support high-speed recording to prevent audio dropouts during sessions.	Must
Stabilisation features	It must be able to place the audio recorder stable in the patient room.	Must

	The audio recorder should have an option to connect it to the camcorder to create a compact and easily transportable setup.	Should
Practical	The audio recorder could be compact and lightweight to facilitate easy transport between patient rooms.	Could
	The microphone and its mounting system must be made of materials that can be easily cleaned and disinfected to comply with hospital infection control protocols.	Must
Appearance	The audio recorder should appear discrete to minimise the feeling of being observed and altering the patient's natural behaviour.	Should
Costs	The audio recorder won't cost more than €200,-.	Won't
	The audio recorder must be as cheap as possible, while reaching the other requirements.	Must