

**INTEGRATING ARTIFICIAL INTELLIGENCE
FOR PERSONALIZED CANCER PAIN
MANAGEMENT: A COMPREHENSIVE STUDY
ON HEALTHCARE PROFESSIONALS'
PERSPECTIVES, DEVELOPMENT OF PAIN
DETECTION METHOD AND USER'S
ACCEPTANCE**

NOOR HASAN IBRAHIM TASHTOUSH

UNIVERSITI SAINS MALAYSIA

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by

NOOR HASAN IBRAHIM TASHTOUSH

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LIST OF ABBREVIATIONS

AdaBoost	Adaptive Boosting Algorithm
AMDI	Advanced Medical and Dental Institute
AMOS	Analysis of Moment Structures
AUC	Area Under Curve
AI	Artificial Intelligence
Ai-PCA	Artificial Intelligent Patient-Controlled Analgesia
AFib	Atrial Fibrillation
AVE	Average Variance Extracted
BP	Blood Pressure
ChatGPT	Chat Generative Pre-Trained Transformer
CNN	Convolutional Neural Networks
ECG	Electrocardiogram
EDA	Electrodermal Activity
EMG	Electromyogram
EMR	Electronic Medical Records
FN	False Negative
Nn	False Negative Value
FP	False Positive
FPR	False Positive Rate
FDA	Food and Drug Administration
GSR	Galvanic Skin Response
HR	Heart Rate
HRV	Heart Rate Variable
IDT	Innovation Diffusion Theory
IPPT	Institut Perubatan dan Pergigian Termaju

ICUs	Intensive Care Units
Int	Intention of Use
IC	Internal Consistency
IQR	Interquartile Range
I-CVI	Item-Level Content Validity Index
I-CVI/Ave	Item-Level Content Validity Index Average
KNN	K- Nearest Neighbors
KAP	Knowledge, Attitude, and Practice
ML	Machine Learning
MLP	Multi-Layer Perceptron
NRSs	Numerical Rating Scales
SpO2	Oxygen Saturation
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
PPG	Photoplethysmography
PI	Principal Investigator
RF	Random Forest
ROC	Receiver Operating Characteristic
RR	Respiratory Rate
S-CVI	Scale - Level Content Validity Index
S-CVI/UA	Scale-Level Content Validity Index/Universal Agreement.
SN	Social Norm
SPSS	Statistical Package for the Social Sciences
SEM	Structural Equation Model
SVM	Support Vector Machines
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior

TSIU	Total Score of Intention to Use
TSEU	Total Score of Perceived Ease of Use
TSPU	Total Score of Perceived Usefulness
TSSN	Total Score of Social Norms
TSUS	Total Score of User Satisfaction Score
TN	True Negative
TP	True Positive
TPR	True Positive Rate
Pn	True Positive Value
UTAUT	Unified Theory of Acceptance and Use of Technology
USM	Universiti Sains Malaysia
US	User Satisfaction
VRSs	Verbal Rating Scales
VR	Virtual Reality
VASs	Visual Analogue Scales
WSD	Wearable Sensing Devices
WHO	World Health Organization

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**MENGINTEGRASIKAN KECERDASAN BUATAN UNTUK PENGURUSAN
SAKIT KANSER YANG DIPERSONALISASI: KAJIAN KOMPREHENSIF
MENGENAI PERSPEKTIF PROFESIONAL KESIHATAN, PEMBANGUNAN
KAEDAH PENGESANAN NYERI DAN PENERIMAAN PENGGUNA**

ABSTRAK

Kesakitan kanser merupakan simptom yang lazim dan menyukarkan yang memberi kesan besar terhadap kualiti hidup pesakit onkologi. Penilaian tradisional terhadap kesakitan sangat bergantung kepada laporan subjektif pesakit, yang mungkin terhad oleh halangan komunikasi atau gangguan kognitif. Dengan kemunculan teknologi boleh pakai, jam tangan pintar menawarkan kaedah yang menjanjikan untuk pemantauan fisiologi secara berterusan dan tidak invasif, sekali gus membolehkan penilaian yang lebih objektif serta sokongan masa nyata. Penyelidikan ini meneroka integrasi kecerdasan buatan (AI) dalam pengurusan sakit kanser secara peribadi melalui tiga fasa. Fasa I meneliti Pengetahuan, Sikap dan Amalan (KAP) serta halangan dalam kalangan profesional kesihatan berkaitan sakit kanser dan penggunaan alat AI melalui temu bual separa berstruktur dengan tiga belas orang doktor dan jururawat yang dipilih secara bertujuan dari Institut Perubatan dan Pergigian Termaju. Temu bual secara mendalam mendedahkan pemahaman yang kukuh terhadap kaedah penilaian sakit secara konvensional dan keterbukaan terhadap penyelesaian berasaskan AI. Walau bagaimanapun, kebimbangan mengenai kepercayaan, latihan, dan infrastruktur muncul sebagai halangan utama kepada pelaksanaan. Fasa II memberi tumpuan kepada pembangunan dan pengesahan model AI untuk pengelasan sakit secara objektif berdasarkan data fisiologi masa nyata yang berterusan (kadar denyutan

jantung, kadar pernafasan, dan tekanan darah) yang dikumpul melalui jam tangan pintar selama 72 jam. Pada peringkat pertama, data semua peserta digunakan untuk melatih model *Support Vector Machine* (SVM) dan *K-Nearest Neighbours* (KNN) bagi mengelas tahap kesakitan. Model-model ini menunjukkan prestasi yang memberangsangkan, terutamanya dalam kes sakit yang teruk, dengan ketepatan SVM mencapai 88% dan KNN mencapai 90%. Dalam peringkat kedua, enam pesakit yang mempunyai data lengkap dan berkualiti tinggi dipilih secara rawak untuk analisis mendalam terhadap corak fisiologi. Data dari pesakit ini disejajarkan dengan episod sakit yang dilaporkan dan dianalisis merentasi empat parameter: kadar denyutan jantung, kadar pernafasan, tekanan darah sistolik, dan tekanan darah diastolik. Prestasi pengelasan terbaik dicapai apabila kadar denyutan jantung dan kadar pernafasan digabungkan, menghasilkan ketepatan antara 70% hingga 90% merentas enam pesakit. Penemuan ini menyerlahkan potensi AI dalam meningkatkan pengesanan sakit kanser melalui corak isyarat fisiologi yang bermakna. Fasa III mengkaji tahap penerimaan peserta terhadap penggunaan jam tangan pintar bagi pemantauan sakit menggunakan Model Penerimaan Teknologi (TAM). Keputusan menunjukkan bahawa persepsi terhadap kegunaan dan kemudahan penggunaan memainkan peranan penting dalam penerimaan teknologi ini, manakala faktor umur pesakit yang lebih tua memberi kesan negatif terhadap persepsi pengguna. Penemuan ini sejajar dengan analisis yang dijalankan khusus untuk pesakit kanser. Secara keseluruhannya, kajian ini menunjukkan bahawa integrasi AI dengan pemantauan fisiologi berasaskan jam tangan pintar boleh melengkapi penilaian sakit secara subjektif, meningkatkan ketepatan, dan berpotensi memperbaiki pengurusan sakit kanser secara individu. Walaupun terdapat kekangan seperti saiz sampel yang kecil, penemuan ini menyediakan asas yang kukuh untuk kajian lanjut. Pengembangan pengesanan model merentas populasi yang

pelbagai dan menangani faktor penerimaan teknologi dalam kalangan klinikal dan pesakit adalah penting untuk memperluas penggunaan pengurusan sakit berasaskan AI dalam persekitaran onkologi klinikal.

INTEGRATING ARTIFICIAL INTELLIGENCE FOR PERSONALIZED CANCER PAIN MANAGEMENT: A COMPREHENSIVE STUDY ON HEALTHCARE PROFESSIONALS' PERSPECTIVES, DEVELOPMENT OF PAIN DETECTION METHOD AND USER'S ACCEPTANCE

ABSTRACT

Cancer pain is a prevalent and distressing symptom that significantly impairs the quality of life in oncology patients. Traditional pain assessments rely heavily on subjective self-reporting, which may be limited by communication, or cognitive impairment. With the rise of wearable technologies, smartwatches offer a promising avenue for non-invasive, continuous monitoring of physiological signals associated with pain, enabling more objective assessment and real-time support. This research explores the integration of Artificial Intelligence (AI) in personalized cancer pain management across three phases. Phase I investigated healthcare professionals' Knowledge, Attitudes, and Practices (KAP) and barriers regarding cancer pain and AI tool adoption through semi-structured interviews with thirteen purposively selected doctors and nurses from Advanced Medical and Dental Institute. In-depth interviews revealed strong understanding of conventional pain assessment methods and openness to AI-supported solutions. However, concerns about trust, training, and infrastructure emerged as critical barriers to implementation. Phase II focused on the development and validation of AI models for objective pain classification based on continuous, real-time physiological data (heart rate, respiratory rate, and blood pressure) collected via smartwatches over a 72-hour period. In the first stage, all participants' data were used to train Support Vector Machine (SVM) and K-Nearest Neighbours (KNN) models to classify pain severity. The models demonstrated promising performance, particularly

in severe pain cases, with SVM achieving 88% accuracy and KNN reaching 90%. In the second stage, a subset of six patients with complete and high-quality data was randomly selected for in-depth analysis of physiological patterns. Data from these patients were aligned with reported pain episodes and analysed across four parameters: heart rate, respiratory rate, systolic, and diastolic blood pressure. The best classification performance was achieved when heart rate and respiratory rate was combined, yielding accuracy rates between 70% and 90% across the six patients. These findings highlight the potential of AI to enhance cancer pain detection by leveraging meaningful physiological signal patterns. Phase III examined participants' acceptance of smartwatches for pain monitoring using the Technology Acceptance Model (TAM). The results showed that perceived usefulness and perceived ease of use significantly influenced adoption, while older age patients negatively affected user perceptions. These findings were consistent with the analysis conducted specifically for cancer patients. Overall, this study demonstrates that integrating AI with smartwatch-based physiological monitoring can complement subjective pain assessments, enhance accuracy, and improve individualized cancer pain management. Despite limitations such as a small sample size, the findings provide a valuable foundation for future research. Expanding model validation across diverse populations and addressing technology acceptance factors among both doctors and nurses and patients will be essential to scaling AI-driven pain management in clinical oncology settings.

CHAPTER 1

INTRODUCTION

1.1 Overview

Cancer is considered a broad category of disease that can begin in any organ or tissue of the body when abnormal cells grow and develop uncontrollably, cross their usual boundaries to invade other regions of the body (Brown et al., 2023), or spread to other organs (Hartl et al., 2023). Mortality from cancer ranked as the second leading cause of death globally, accounting for an estimated 9.7 million deaths in 2022 (Bray et al., 2024). Among men, the most prevalent types of cancer are lung, prostate, and colorectal cancers, whereas among women, breast, colorectal, and lung cancers are the most commonly diagnosed (Da Cunha et al., 2023). However, the pain associated with the presence of the cancer is related to the intensity and severity of the cancer in the human body.

Cancer pain in the human body may result from the direct biological effects of the tumour or emerge as a side effect of chemotherapy treatment (Haroun et al., 2022). Cancer pain is a complex and multifaceted experience that can arise from the cancer itself, such as tumours pressing on bones, nerves, or organs, or from treatments like surgery, chemotherapy, and radiation. This pain can vary widely in intensity, from mild to severe, and can be constant or intermittent. It is not just a physical challenge; it deeply affects emotional and psychological well-being, impacting a patient's quality of life and their ability to engage in daily activities, not only for patients, but also for families, communities, and healthcare systems (Cascella et al., 2023; Haroun et al., 2022).

Achieving optimal outcomes in cancer pain management requires full assessment to guide appropriate interventions. This includes identifying patient-specific goals beyond pain intensity, such as those related to mood, function, and quality of life, which are often under-assessed in current practice despite their relevance to personally meaningful pain relief (Ehrlich et al., 2024; Luckett et al., 2013).

1.2 Artificial Intelligence in Medicine and Pharmaceutical Sciences

Artificial intelligence (AI) has revolutionized the analysis of complex medical data, including patient records, medical imaging, and genetic profiles, allowing researchers and healthcare professionals to identify hidden patterns and estimate disease outcomes (Hu et al., 2019). This advancement supports more accurate diagnoses, individualized treatment planning, and ultimately better patient outcomes (Casella et al., 2023).

Recent advancements in pharmaceutical sciences have significantly transformed the processes of drug discovery, design, and development. By processing huge amounts of chemical and biological data, including molecular structures, gene expression profiles, and clinical trial results, advanced algorithms can identify potential drug candidates and predict their efficacy and safety (Vora et al., 2023). These technologies have notably reduced both the time and cost associated with drug development, while improving clinical trial success rates. They are also enabling pharmaceutical companies to enhance drug production processes, streamline supply chain management, and ensure greater safety and efficacy throughout the drug development (Yadav et al., 2024).

Clinical pharmaceutical research has likewise benefited. Through deep analysis of gene expression data and molecular configurations, AI helps predict disease progression and identify novel therapeutic targets (Ranchon et al., 2023; Zeinali et al., 2024). These capabilities not only accelerate research timelines but also enable the design of more precise, personalized treatment protocols (Taherdoost et al., 2024; Topol, 2019). Furthermore, pharmaceutical companies have enhanced supply chain management and ensured medicine safety and efficacy through AI. Clinical pharmacy research is now faster and more accurate by using AI (Ranchon et al., 2023).

1.3 Technologies Used in Measuring Pain

Wearable Sensing Devices (WSD) are smart electronic devices that can be worn on the body as implants or accessories and have drawn much research attention in recent decades. Many factors influence the technology of WSD, mainly the functionality, the size, the real-time applications, and the quick growth of production technologies and sensor technology, which are rapidly improving (Dong et al., 2021). WSD devices have been employed for many diseases and disorders; cancer-related devices have been developed by determining the physiological parameters and are Food and Drug Administration FDA-approved for monitoring the progression of cancer, such as biochip technology (Nunna et al., 2017).

Many computer and mobile technologies have been integrated into various diseases to allow full self-management of those conditions. In a study by Pavic et al. (2020) remote monitoring of palliative cancer patients using smartphones and sensor-equipped bracelets was evaluated, they found that most feedback about using the smartphone and the sensor-equipped bracelet monitoring system was positive (Pavic et al., 2020). However, users reported several issues, including Bluetooth

disconnections, app crashes, frequent device restarts, and discomfort wearing the bracelet, particularly during sleep or in hot weather. Additional concerns included the lack of a battery indicator, frequent charging, difficulties among older patients with limited digital experience, and the absence of real-time health data feedback (Pavic et al., 2020).

A narrative review by Naranjo-Hernández et al. (2020) reported studies that used sensors to measure and detect non-cancerous chronic pain for objective evaluation, and demonstrated many studies attempted to evaluate pain by inducing it in a controlled manner (pressure, heat, cold, or electrical). The review provided a comprehensive overview of research approaches, ranging from video signal processing or bio-physiological signal analysis to systems that incorporate heterogeneous sources of information. Also, a detailed review of sensor technologies and physiological aspects relevant to underlying chronic pain assessment technologies, whether musculoskeletal, fibromyalgia, migraine, or other forms of non-oncological chronic pain, is given. Although pain is a personal and subjective feeling, the narrative review shows that using several body signals together with machine learning can help measure pain more accurately (Naranjo-Hernández et al., 2020).

1.4 Problem Statement and Rationale of Study

Pain is typically the major source of complaint that prevents patients from enjoying their regular lives; the literature lacks objective parameters and methods for measuring pain (Haroun et al., 2022); the current methods are subjective and depend on patients' descriptive inputs (Forte et al., 2022); the situation becomes more complicated when patients cannot describe their pain (El-Tallawy et al., 2023; Haefeli & Elfering, 2006). In this regard, this study aims to develop a new pain assessment

model using smartwatches and artificial intelligence by collecting physiological parameters to enable fast, accurate, and personalized pain detection.

The aspects that define pain and its effects are pain intensity, pain-related disability, duration of pain, and pain effect (Williamson & Hoggart, 2005). Different evaluating instruments exist for each aspect, and several studies have discussed the benefits and drawbacks (Naranjo-Hernández et al., 2020).

One of the reasons patients experience poorly managed pain is that many healthcare professionals lack adequate training in pain assessment and management, resulting in suboptimal pain control (Alkhatib et al., 2020; Ortiz et al., 2022; Ung et al., 2016). Lack of assessment is the most common barrier to successful pain management (Rababa et al., 2021). In addition, healthcare workers frequently lack sufficient knowledge regarding pain assessment and analgesic usage. There are still many myths and misconceptions about opioids, tolerance, and addiction (Rababa et al., 2021). For example, the belief that using opioids for cancer pain certainly leads to addiction, that physical dependence equates to substance abuse, or that escalating doses always signal misuse rather than clinical necessity (Paice, 2018; Wu et al., 2025).

Despite the rapid development of artificial intelligence (AI) technologies in healthcare, there remains a significant gap in understanding how healthcare professionals perceive and integrate these tools, particularly in pain management, where subjective reporting often leads to inconsistent care quality. Current evidence suggests that the adoption of AI-enhanced pain assessment devices is limited, partially due to insufficient knowledge, uncertain attitudes, and inconsistent practices among medical staff. To address this, our study employs the Knowledge, Attitude, and Practice (KAP) model and barriers to explore how healthcare professionals

understand, respond to, and implement AI-based solutions in clinical pain evaluation and management.

Additionally, while AI-based pain detection smartwatches have shown promising results in objective pain measurement, little is known about patients' acceptance of such technologies, especially those involving wearable sensors. The Technology Acceptance Model (TAM) is therefore applied to identify the factors influencing users' willingness to use these devices, particularly perceived usefulness, ease of use, and intention of use, highlighting potential barriers to widespread implementation.

The KAP questionnaire and the TAM method target is to discover the factors that impact the use of new AI technology in pain management. However, the KAP question guide in phase I of our study focuses on the reaction of healthcare professionals. At the same time, the TAM method in phase III of this study represents users' perceptions of usefulness, ease of use, and their willingness to adopt AI-based solutions for managing pain.

This study aims to explore and assess healthcare professionals' knowledge, attitude, practices, and barriers regarding adopting sensor-based diagnostic device in current medical environments. Moreover, proper classification of pain is proposed and developed to label participants into different pain levels and measure pain in cancer patients, providing a clear description of their pain intensity. Ultimately, we aimed to measure the level of acceptance of technology among both participants and patients regarding the use of smartwatches for health monitoring and pain assessment in cancer patients. To explore this, TAM was employed to examine the factors influencing the intention to use smartwatch devices.

Smartwatch-based tracking in this study collects different physiological indicators such as heart rate, blood pressure, sleep quality, and physical activity. In addition, the smartwatches are used with pain assessment tools (self-report logs) to help monitor and document cancer-related pain.

This study aims to bridge the gap between current practices and potential technological advancements in cancer pain management. By addressing these issues, the research seeks to improve pain management for cancer patients, ultimately enhancing their quality of life and care outcomes.

1.5 Research Questions (RQ)

- RQ1. What is the level of knowledge, attitude, practice, and perceived barriers among healthcare professionals regarding cancer pain management in Malaysia?
- RQ2. What physiological parameters can be used to develop a model for detecting, measuring, and classifying cancer-related pain?
- RQ3. How can Artificial Intelligence (AI) be employed for the accurate classification of different levels of cancer-related pain?
- RQ4. What is the level of technology acceptance among study participants toward the use of smartwatches as an AI-based tool for pain management, including their perceived usefulness and ease of use?

1.6 Research Objectives (RO)

- RO1. To explore the knowledge, attitude, practice, and perceived barriers among healthcare professionals regarding cancer pain management in Malaysia.
- RO2. To identify relevant physiological parameters collected by smartwatches for detecting, measuring, and classifying cancer-related pain.
- RO3. To classify cancer pain intensity using artificial intelligence models.
- RO4. To evaluate participants' acceptance regarding the use of smartwatches as an AI-based tool including perceptions of their usefulness and ease of use.

1.7 Significance of the Study

Pain management is evident given the realization that more people suffering from pain, chronically and consistently, which imposes more challenges to the healthcare system and incurs health implications for the patient. Increased use of healthcare services, hospital stays, emergency room visits, and financial hardship have been linked to uncontrolled pain (Park et al., 2023; Zhang et al., 2023). Research supports the integration of AI in identifying, diagnosing, and managing pain to improve clinical outcomes and optimize resource utilization.

To control pain, researchers have promoted AI methods for identifying, diagnosing, and treating pain may enhance patient outcomes and the efficient use of medical resources (Zhang et al., 2023). The introduction of AI approaches for

recognizing, diagnosing, and treating pain holds promise for improving patient outcomes and making better use of medical resources, offering a hopeful future for healthcare (Park et al., 2023).

This study holds significant value in addressing the challenges of cancer pain assessment and management by exploring KAP and perceived barriers among healthcare professionals. By leveraging physiological data collected through scientific smartwatches, the study applies AI models to classify and assess pain intensity more accurately. Furthermore, the study evaluates the acceptance and perceived usability of AI-driven tools using TAM by participants. These insights are essential for assessing the feasibility of integrating wearable AI technologies into routine clinical settings.

1.8 Conceptual Framework

The conceptual framework presented in Figure 1.1 is organized into three integrated phases. Phase I adopts the KAP model to explore healthcare professionals' knowledge, attitude, clinical practice, and perceived barriers related to cancer pain assessment and management. Knowledge serves as a cognitive foundation that informs attitudes and practices, though the relationship is dynamic and reciprocal. The results obtained from phase I laid the groundwork for the second phase, highlighting the need for technology-supported approaches to enhance cancer pain management.

In Phase II, ML models were developed using physiological data collected via smartwatches (e.g., heart rate, blood pressure, and oxygen saturation) to detect and classify pain levels in patients. This data-driven approach established baseline trends in healthy individuals and identified deviations in cancer patients to enhance pain detection accuracy. Building on this, Phase III applied TAM to assess participants'

acceptance of smartwatches for pain monitoring. Key constructs, perceived usefulness, ease of use, social influence, and user satisfaction, were used to determine user intention to adopt the AI-based technology. By linking healthcare professionals' readiness (KAP) with AI implementation and patient acceptance (TAM), this framework offers a comprehensive pathway to improve cancer pain management through technology adoption.

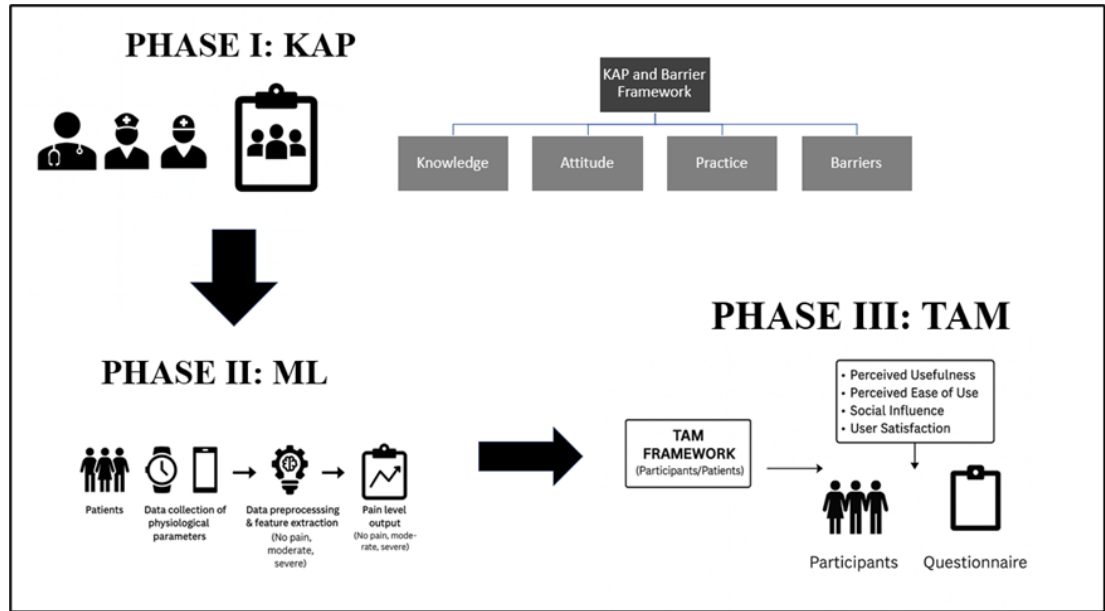


Figure 1.1 Conceptual Framework of Study Phases

1.9 Operational Definition

Quantitative Analysis: The use of data collected from the questionnaires in statistical quantitative analysis to deduce the statistical significance of the attitude toward using the smartwatch by community.

Qualitative Analysis: A research method used to gather and interpret non-numerical data such as text, audio, or video. This approach aims to understand

underlying reasons, opinions, and motivations by identifying patterns, themes, and meanings within the data.

The Pain Classification: The Pain Classification System represents the output of an AI algorithm designed to detect and categorize cancer-related pain objectively. It analyses deviations in physiological parameters between healthy participants and patients experiencing pain to classify pain levels (e.g., no pain, moderate, severe).

The AI algorithm: AI algorithm is an adapted machine learning algorithm that will learn and forecast the pain scale by measuring the distance between the normal and abnormal.

Numerical Rating Scale (NRS): scale ranges from 0, indicating no pain, to 10, indicating extreme pain, with two increments (0, 2, 4, 6, 8, 10) (Falch et al., 2014).

Healthy participants: Individuals who do not suffer from any pain. In other words, based on NRS, the study selects participants whose rating on the NRS is 0.

Events: Each event in the dataset represents a single observation of physiological data captured by the smartwatch for a participant. These events include heart rate, respiratory rate, and systolic and diastolic blood pressure.

CHAPTER 2

LITERATURE REVIEW

2.1 Cancer Pain

2.1.1 Cancer Pain Definition and Classification

Pain, characterized as "a sensory and emotional experience linked to actual or potential tissue damage, or described in terms of such damage," is a prevalent symptom among cancer patients (Swarm et al., 2010). Cancer pain is defined as chronic pain resulting from the primary cancer itself, its metastases, or its treatment (Bennett et al., 2019). It should be distinguished from pain caused by other comorbid conditions by the intensity and most importantly by the episode time of pain; chronic pain is more persistent and tend to span over longer episode's periods (Grichnik & Ferrante, 1991). Over the last few decades, cancer pain has become a significant as a critical healthcare concern due to its complex, multidimensional nature and the variety of physiological, psychological, and social factors that influence it (Zaza & Baine, 2002).

Cancer-related pain is distinct from pain experienced by individuals without malignancies affecting approximately 25% of newly diagnosed cancer patients, 33% of those undergoing treatment, and 75% of patients with advanced disease stages prevalence (Deandrea et al., 2008; Van Den Beuken-Van Everdingen et al., 2016). Cancer patients' source of pain is mainly attributed to the pressure resulting from the tumour to the surrounding tissues; other reasons of the pain associated with cancer is either related to the chemotherapy treatment, or the inflammation related to the increase of cell sensitivity (Evenepoel et al., 2022). Inadequately managed pain deprives patients of comfort and significantly impacts their daily activities, motivation, social interactions, and overall quality of life (Nayak et al., 2017).

2.1.2 Cancer Pain Prevalence

Cancer is becoming a prevalent disease, with about twenty million new cases recorded each year worldwide (World Cancer Day, 2023). In Malaysia, more than 50,000 cases are registered annually, and there has been a prevalence of more than 150 cases over the past five years (Ferlay & Ervik, 2024). Cancer remains a significant public health concern, contributing to approximately 16,500 to 20,000 deaths annually in Malaysia (Department of Statistics Malaysia, 2023). The latest report from the National Cancer Registry indicates a rise in new cases identified, with breast cancer being the most common, followed by colorectal cancer (Ferlay et al., 2024)

A particularly concerning aspect of this report is the increase in cases that are detected late, at stages 3 and 4 (Cancer Registry Report, 2021). About 50% of cancer-related pain affects cancer patients who suffer from moderate to severe pain, and pain has been considered as one of the most frequent and complex symptoms affecting cancer patients (Caraceni & Shkodra, 2019; Haenen et al., 2023).

Recent evidence confirms that pain remains a prevalent and serious issue among cancer patients. According to a comprehensive systematic review and meta-analysis by Snijders et al. (2023), which included 444 studies published between 2014 and 2021, approximately 44.5% of cancer patients experience pain, and 30.6% report moderate to severe pain. This study covered patients across all phases of the cancer trajectory, treatment-naïve, under curative or palliative care, post-treatment, and those with advanced disease, offering a reliable and current estimate of cancer pain prevalence globally. The findings emphasize the ongoing burden of cancer-related pain and the continued need for effective pain assessment and management strategies (Snijders et al., 2023).

The prevalence of pain among cancer patients varies extensively and is expressed using several metrics that describe different types of cancer and their extent, the population assessed, and the type of treatment (Logan et al., 2019; Magee et al., 2019). The estimated frequency of chronic pain in cancer patients undergoing cancer treatment is up to 80%, and it is considerably higher in patients with advanced cancer stages (Gulati, 2021; Logan & Cluxton, 2019).

Uncontrolled pain is related to poor outcomes and delayed recovery (Gulati, 2021). Although cancer pain is manageable in many cases, effective management depends on accurate assessment and appropriate treatment. Pain assessment typically relies on subjective methods, such as self-reported pain scales, to evaluate pain severity. In contrast, pain treatment involves the use of pharmacological and non-pharmacological interventions aimed at reducing pain intensity while minimizing side effects (Gress et al., 2020). Existing evidence suggests that almost half of the cancer patients in the developed world obtain suboptimal pain management (Gulati, 2021; Liu et al., 2023; Saini & Bhatnagar, 2016). One of the most critical barriers to achieving effective cancer pain control is the lack of a reliable and validated pain assessment system. Inadequate assessment often leads to under-treatment or mismanagement of pain (Saini & Bhatnagar, 2016).

Cancer pain involves a broad range of causes, characteristics, and pathophysiological mechanisms, making its evaluation complex (Moscato, Cortelli et al., 2022). Accurate pain assessment is widely recognized as the cornerstone of effective pain management, particularly in oncology settings where pain can significantly impair quality of life (Caraceni & Shkodra, 2019). Over the years, multiple guidelines have emphasized the need for comprehensive pain assessment before initiating management strategies. In response to this need, various validated

assessment tools such as the Numerical Rating Scale (NRS), Verbal Rating Scale (VRS), and Visual Analog Scale (VAS) have been developed (Brunelli et al., 2010; Hjermstad et al., 2011; Knudsen et al., 2011). These tools facilitate the measurement of pain intensity across different clinical contexts and support individualized treatment. Despite their utility, these instruments rely heavily on subjective self-reporting, which may introduce variability and limit their precision in certain populations, especially those with cognitive or communication impairments. This challenge highlights the rationale for integrating more objective, technology-enhanced approaches, such as AI-based physiological monitoring, to supplement traditional methods and enhance the accuracy of cancer pain classification and management strategies (Cascella et al., 2025; Dave, 2024; Ghane et al., 2025).

Cancer pain continues to have a significant negative impact on patients' quality of life, particularly in those with advanced disease stages. Despite some decline over the years, the overall prevalence remains high, with recent estimates indicating that approximately 40% of all cancer patients experience pain, and more than half of those in advanced stages report moderate to severe pain, regardless of the underlying cause (Mestdagh et al., 2023; Snijders et al., 2023; van den Beuken-van Everdingen et al., 2007). Patients complain that pain prevents them from focusing or thinking and makes routine everyday tasks difficult. More than one-third of patients describe cancer pain as distressing or even unbearable (Snijders et al., 2023). Evidence shows sufficient pain management leads to clinically meaningful changes in the quality of life associated with health (Snijders et al., 2023)

2.2 Cancer Pain Assessment and Scales

In the past decade, identifying risk factors that contribute to the development and persistence of cancer pain, mainly psychological and psychosocial influences, has become a significant focus in pain management research. These factors can strongly shape how patients perceive, report, and respond to pain, thus influencing both clinical assessment and outcomes (Crombez et al., 2023). In today's hospital environment, pain measurement and management have become crucial (Al-Sayaghi et al., 2022). Poor pain management is associated with decreased well-being, diminished patient satisfaction, and increased healthcare costs (Dueñas et al., 2016).

Untreated pain can worsen patient outcomes, reduce the quality of life, decrease patient satisfaction, and increase hospital costs (Muzellec et al., 2021). Patients with uncontrolled or inadequately managed postoperative pain, compared to those who receive adequate analgesia, tend to experience more extended hospital stays, higher rates of unanticipated readmissions, and more frequent outpatient visits. These outcomes contribute to increased healthcare costs and significantly impact patient satisfaction and quality of life (Baratta et al., 2014).

Managing pain has many advantages, such as decreasing the patient's pain, speeding up recovery, enhancing sleeping, increasing the patient's mobility, and increasing patient satisfaction and outcome (Glowacki, 2015). Consequently, pain management can lead to shorter hospital stays, fewer readmissions, and improved patients' overall quality of life. Hospital environments have become progressively aware of the importance of pain management (Trail-Mahan et al., 2016).

Evaluating pain is crucial for understanding its nature and the underlying mechanisms, thus facilitating informed decision-making in medical treatment. A full pain history and thorough clinical examination are fundamental to pain assessment (Caraceni & Shkodra, 2019). Key pain attributes such as intensity, spread, duration, temporal fluctuations, qualities, and factors that provoke or alleviate pain are essential for effective management. Employing mnemonics like SOCRATES (Site, Onset, Character, Radiation, Associated factors, Timing, Exacerbating/relieving factors, and Severity) offers a structured approach in clinical settings to systematically assess pain characteristics (Caraceni & Shkodra, 2019; Rayment & Bennett, 2015).

2.2.1 Subjective Pain Assessment

Subjective cancer pain assessment remains a crucial yet complex aspect of oncology care, given the inherently personal nature of pain perception and its significant impact on a patient's quality of life (Gomes-Ferraz et al., 2022). Traditional methods, such as self-report questionnaires and numerical rating scales, provide valuable insights into the patient's pain experience but are often limited by their reliance on patient communication and subjective interpretation (Gomes-Ferraz et al., 2022).

2.2.1(a) Unidimensional Pain Scale Tools

Assessing pain is a critical issue in healthcare. Patient-reported outcomes are considered the most valid and reliable measures of pain, leading to the development of various tools for this purpose. These tools are designed to measure pain intensity using a single metric and are commonly used in various clinical contexts due to their simplicity, ease of use, and proven reliability. Figure 2.1 illustrates the most widely

used unidimensional pain assessment scales: the Visual Analogue Scale (VAS), Numeric Rating Scale (NRS), Verbal Rating Scale (VRS), and Faces Pain Scale (FPS) (Falch et al., 2014).

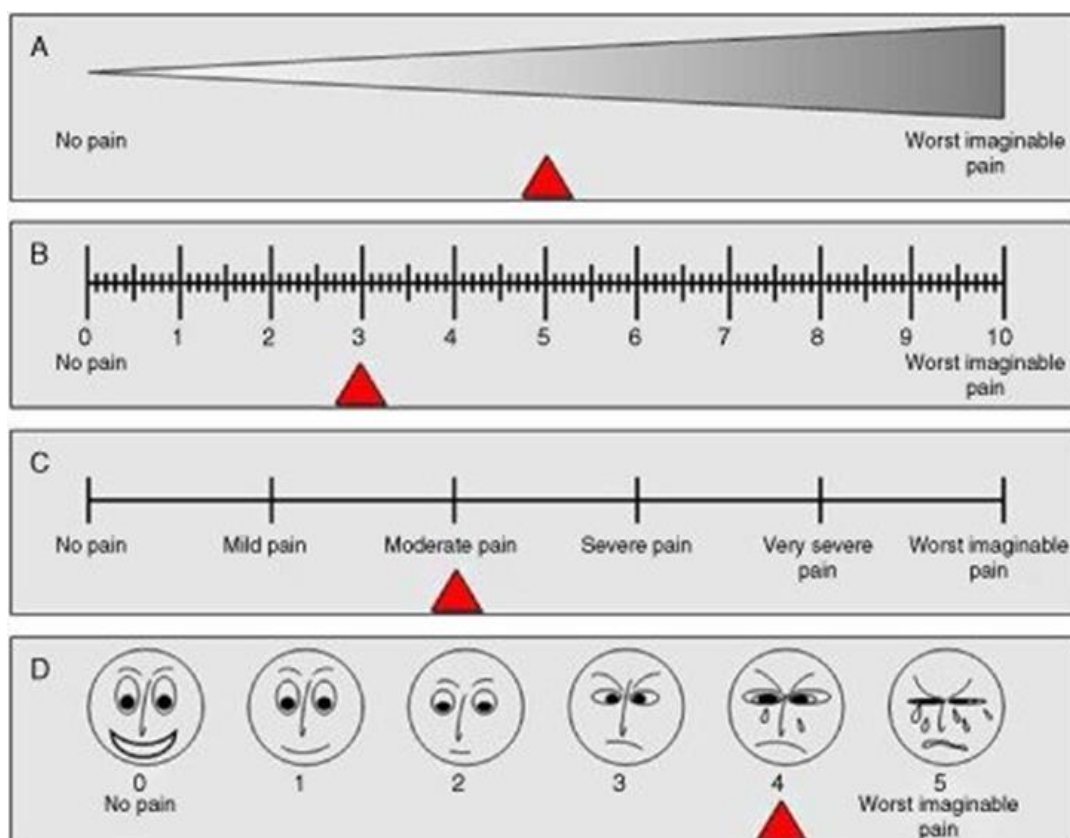


Figure 2.1 Examples of Unidimensional Pain Ratings Scales

(A) Visual analogue scale (VAS) (B) Numerical rating scale (NRS) (C) Verbal rating scale (VRS) (D) The Faces Pain Scale (FPS)

Adapted from (Falch et al., 2014), Treatment of acute abdominal pain in the emergency room: a systematic review of the literature. *European Journal of Pain* (London, England), 18(7), 902–913. <https://doi.org/10.1002/J.1532-2149.2014.00456.X> with permission.

2.2.1(a)(i) Visual Analogue Scale (VAS)

The VAS consists of a horizontal or vertical line, typically 100 mm in length, with anchors at each end indicating "no pain" and "worst pain imaginable." Patients mark a point along the line that reflects their current pain intensity. This scale is

particularly useful in cancer pain assessment but has limitations. It requires basic numerical and visual interpretation skills and may be unsuitable for patients with cognitive impairment or language barriers. Furthermore, it does not capture other dimensions of pain, such as quality, duration, or impact on daily activities. As a result, interpretation can vary, for example, what constitutes a 50/100 or 70/100 score may differ between patients or healthcare professionals (Brunelli et al., 2010; Hjermstad et al., 2011; Waterfield & Sim, 1996).

2.2.1(a)(ii) Numeric Rating Scale (NRS)

The NRS simplifies pain assessment by asking patients to rate their pain on a scale from 0 (no pain) to 10 (worst possible pain). It consists of a single question, requires minimal explanation, and causes little patient distress. The NRS is highly sensitive and is frequently used for clinical auditing and further analysis (Karcioglu et al., 2018). Its straightforward nature makes it one of the most commonly used tools in both cancer and non-cancer pain contexts.

2.2.1(a)(iii) Verbal Rating Scale (VRS)

The VRS uses verbal descriptors instead of numbers. Patients choose from categories such as “None,” “Mild,” “Moderate,” and “Severe,” and in some versions, “Worst possible pain” is added, forming a 0–4 scale. This scale is especially beneficial for populations with limited literacy or cognitive challenges, as it avoids the need for numerical understanding. Each descriptor has demonstrated high reliability and validity among adult populations, making it suitable for various clinical settings such as acute care, geriatrics, and palliative care (Hartrick et al., 2003; Thong et al., 2018).

2.2.1(a)(iv) Faces Pain Scale (FPS)

The FPS uses a series of facial expressions ranging from a happy face (no pain) to a crying face (worst pain) to help patients visually express their pain intensity. It is especially useful for children and those with communication difficulties. While it is visually based like the VAS, the FPS does not require abstract numerical thinking, making it more accessible for certain patient populations (Hjermstad et al., 2011).

2.2.1(a)(v) Overall Comparison of Unidimensional Pain Assessment Scales

Table 2.1 provides a comparison of these tools in the context of cancer pain assessment. While primarily discussed here in relation to cancer pain, these tools are also widely applied in postoperative, chronic non-cancer, and musculoskeletal pain assessments.

Table 2.1 Comparison of Pain Assessment Methods

Assessment Method	Technical Description	Advantages	Disadvantages
Visual Analog Scale (VAS)	A 10 cm line where patients mark their perceived pain intensity, ranging from 0 (no pain) to 100 mm (worst possible pain)	- Easy and quick to administer. - Provides a continuous scale of pain intensity	- Requires numerical ability, limiting its use among patients with cognitive impairments. - Not sensitive to mild pain. - Subjective interpretation may vary
Numerical Rating Scale (NRS)	A single question scale ranging from 0 (no pain) to 10 (worst possible pain)	- Simple and easy to understand. - Low patient distress. - Useful for data audits and analysis	- Subjective nature can lead to inconsistent assessments. - Limited information on pain quality, location, or duration

Table 2.1 (Continued)

Assessment Method	Technical Description	Advantages	Disadvantages
Verbal Rating Scale (VRS)	Patients select from a set of descriptors (e.g., none, mild, moderate, severe)	- Easy to understand without requiring high cognitive ability. - No numerical literacy required	- Limited sensitivity compared to other methods. - Subjective categorization of pain can lead to variability
Faces Pain Scale (FPS)	Uses facial expressions to represent pain intensity, mainly for children	- Effective for non-verbal patients, children, and those with communication difficulties	- Limited to basic pain levels - Cannot assess other pain dimensions like quality or duration
Our study AI-Based Model (Smartwatch + AI)	Uses physiological parameters (HR, BP, RR,) collected via wearable; classified using ML models	- Provides objective, continuous, and real-time pain assessment - Not limited by language or literacy - Can detect pain patterns over time	- Requires initial calibration - Needs validation in clinical settings

2.2.1(b) Multidimensional Pain Assessment Tools

Multidimensional pain assessment tools broadly evaluate a patient's pain experience by considering various aspects beyond intensity. These tools, such as the McGill Pain Questionnaire (Melzack et al., 2001) and the Brief Pain Inventory (Cleeland et al., 1994; Kumar, 2011), assess multiple dimensions of pain, including quality, location, duration, and impact on daily activities (Caraceni et al., 2002). The multidimensional pain assessment tools are time-consuming, require more training, and are sensitive to social norms, which results in creating more subjective assessment tools that suffer from low accuracy despite their comprehensiveness (Tsu et al., 2010). For example, the Brief Pain Inventory typically takes about 10 minutes to administer,

and studies have shown that patients often fail to complete it correctly (Driscoll et al., 2017; Scher et al., 2020; Waldman, 2011)

2.2.2 Objective Pain Assessment

Recently, there has been a strong focus on objective pain detection using various technologies. One effective approach involves the automated recognition of pain through facial expressions, which has demonstrated effectiveness and efficiency in multiple studies (Cascella, Vitale, et al., 2023; Semwal & Londhe, 2020; Swetha et al., 2022). Remarkably, this technology can even be applied to patients in intensive care units (ICUs) who are on mechanical ventilation despite the challenges of assessing pain in such a challenging environment (Yuan et al., 2023).

Another way of research has utilised physiological signals and wearable sensors, including electrocardiogram (ECG), electromyogram (EMG) (Jerritta et al., 2022; Phan et al., 2023), and electrodermal activity (EDA) (Kong et al., 2022), for pain assessment. These studies collectively suggest that machine learning models can accurately classify different pain levels, making wearable technology a viable option for real-time and continuous pain monitoring. In a different approach, advanced technology has been used in specific settings, such as post-anaesthetic patients, where computational techniques are employed to provide a more objective and personalised pain analysis (Ghita et al., 2023). This involves deep learning with Convolutional Neural Networks (CNN) using time-frequency data and spectrograms, with inputs derived from skin impedance measurements. The study concludes that this tailored online identification and deep learning approach can help prevent overdosing of analgesics (Ghita et al., 2023).

In another study, Virtual Reality (VR) sessions were used (Moscato, Orlandi, et al., 2022). Physiological signals, including photoplethysmography (PPG), electrodermal activity, skin temperature, and accelerometer data, were recorded using an Empatica E4 wristband. Pain ratings were obtained before each VR session, and machine learning classifiers like Support Vector Machine (SVM), Random Forest (RF), Multilayer Perceptron (MP), Logistic Regression, and Adaptive Boosting Algorithm (AdaBoost) were applied for classification. The results demonstrated that these physiological signals can be used to assess pain, with the best-performing model achieving 72% accuracy in distinguishing between 'pain' and 'no pain' classes. This supports the feasibility of using wearable sensor data for objective pain assessment in real-world settings (Moscato, Orlandi, et al., 2022)

Furthermore, another study focused on pain recognition using physiological signals with different datasets, such as the BioVid heat pain dataset and EmoPain dataset (Phan et al., 2023). The results indicated that the KNN classifier outperformed the RT classifier in assessing no pain and high pain, and EMG signals were found to be more informative than Heart Rate Variable (HRV) signals (Phan et al., 2023). Uddin et al. (2023) proposed a cooperative learning framework for wearable-based pain assessment, emphasizing its effectiveness in delivering personalized and context-aware evaluations (Uddin et al., 2023).

Recent studies show the importance of using physiological signals to measure pain. In 2022, a systematic review by Moscato et al. comprehensively discussed the physiological responses to pain. Among the 16 parameters analysed, electrocardiography (ECG) and blood pressure (BP) were the most commonly utilized signals, current research supports the idea that physiological signals, particularly ECG and blood pressure, can contribute to the partial objective assessment of pain in cancer

patients (Moscato, Cortelli, et al., 2022). In 2023, a scoping review by Zhang et al. recommended that using AI-based interventions has a positive effect on pain recognition, pain prediction, and pain self-management; however, more pilot studies using physiological measures are needed before larger-scale studies, including clinical trials and other research designs, can be conducted (Zhang et al., 2023).

Another study highlights the importance of using AI in pain detection and emphasizes its advantages in objectively measuring and understanding pain. AI holds significant promise in advancing pain assessment by offering standardized and scalable methods that address the limitations of traditional self-reporting. Techniques such as image recognition, neurophysiological signal analysis, and natural language processing enable more accurate pain detection, particularly in patients who have difficulty communicating (Cascella et al., 2023).

2.3 Cancer Pain Management and Patient's Quality of Life

Several recent studies emphasize that effective pain and symptom management using digital and personalized tools significantly enhances the quality of life for cancer patients. Hamdoune et al. (2024) conducted a systematic review of digital health technologies used in palliative oncology care and concluded that such tools, like PainCheck and Mobile Palliative Care Link, improve patients' ability to monitor symptoms, adhere to treatment, and communicate more effectively with healthcare professionals. These technologies were shown to support real-time assessment of pain and related symptoms such as fatigue and anxiety, all of which directly impact patients' daily functioning and well-being. The review identified improved QoL outcomes across different countries and settings, especially when digital tools facilitated remote care and reduced unnecessary hospital visits (Hamdoune et al., 2024).