**Unraveling the Patient-AI Nexus: A Triangulated Phenomenological Exploration of Psychological Themes in Patient Interaction with AI**

1. **Scientific Background:**

Artificial Intelligence (AI), including advanced machine learning (ML), is expected to profoundly impact healthcare in the near future by offering breakthrough improvements in the diagnosis, treatment, and overall management of healthcare services. However, this extraordinary potential comes with a heavy responsibility to ensure that the development and deployment of AI technologies are grounded in the realities of patients' needs and experiences, thereby promoting patient-centered innovation. Integrating AI into healthcare encompasses deep psychosocial considerations while navigating the complex ethical and moral landscape that accompanies it.

There is a significant knowledge gap in the current understanding of how patients perceive and respond to the use of AI tools in healthcare. While AI technology is increasingly integrated into clinical settings and used for health purposes, user experiences and interactions are mainly examined among physicians rather than patients. Research is required to explore various phenomena related to the interaction between patients and health-related AI applications. Exploring patients' emotions and perceptions related to AI use in healthcare and understanding how patients capture autonomy and decision-making in the presence of AI is crucial for creating patient-centered systems and fostering confidence in technological advancements in medicine.

This research proposal suggests the implementation of a triangulated qualitative approach to facilitate a comprehensive, in-depth analysis of the underlying psychological themes involved in patient-AI interactions. While current models often focus on the technical aspects of AI implementation, a detailed understanding of the human side in patient-AI interactions in the context of health, where decisions can affect life and death, will make a critical theoretical contribution to the field. This research project thus aims to develop a new theoretical model that will fill the existing knowledge gap related to patient-AI interaction, thereby contributing to and enriching the broader body of knowledge pertaining to human-technology interactions and health psychology. This model may lay the groundwork for the future development of tools to research and promote the alignment of AI advancements with psychosocial factors and patient values.

1. **Artificial intelligence applications in healthcare**

As an ecosystem, the healthcare industry has recognized the importance of adopting AI systems to improve quality and achieve optimal health outcomes. There is a consensus that AI has the potential to revolutionize patient care through precision medicine and patient-centered care delivery (Akinrinmade et al., 2023). In the last few years, AI has made significant strides in the healthcare industry, changing how medical professionals diagnose, treat, and manage patient care. The current implementations of AI technologies are reshaping clinical practices, improving efficiency, and addressing healthcare challenges. Some of the most important applications of AI in healthcare at present are discussed below.

Diagnosis: One of the primary areas in which AI has widely applied is assisting clinicians in disease diagnosis and treatment planning. AI algorithms significantly improve the accuracy and speed of diagnostic efforts, enabling early detection and improved patient outcomes (Aldali et al., 2024; Aftab et al., 2024). AI-based systems powered by advanced ML algorithms can analyze large datasets of medical images, such as X-rays, MRI scans, and pathology slides, to detect anomalies and identify potential health issues with remarkable accuracy (Lee & Yoon, 2021; Thieme et al., 2023; Maleki et al., 2024). Deep-learning algorithms, a subset of ML in which multilayered neural networks learn from vast amounts of data, have shown remarkable accuracy when used to interpret medical images (Ardila et al., 2019; Esteva et al., 2017). AI continuously facilitates the development of tailored treatment plans by analyzing patient data and enhancing the effectiveness of medical interventions (Jangra & Singh, 2024).

Prediction and decision-making: AI systems are increasingly being used to support clinical decision-making. Beam and Kohane (2018) reviewed the potential of ML in clinical medicine and highlighted its utility for predicting disease onset and progression. AI has shown promise as a means of extracting meaningful insights from vast electronic health record (EHR) data. Rajkumar et al. (2018) developed a deep-learning model that could predict clinical outcomes, including in-hospital mortality and readmission, using EHR data that demonstrated high accuracy across multiple institutions. AI-driven tools can predict patient outcomes such as hospital length of stay, readmission risk, and mortality, enabling healthcare providers to make more informed decisions and optimize resource allocation.

Personalized Treatment: AI facilitates the advancement of personalized medicine. Topol (2019) reviewed how AI can integrate diverse datasets, including genomics, to provide personalized treatment recommendations and predict individual patient responses to therapies. Moreover, AI is being utilized to aid the interpretation of genomic data, helping researchers and clinicians better understand the genetic factors that contribute to disease susceptibility and progression (Quazi, 2022). AI applications are also emerging in mental healthcare (Fitzpatrick et al., 2017), enhancing diagnostic processes, continuous monitoring, and personalized mental healthcare experiences, while also assisting individuals in managing mental illnesses such as depression (Talati, 2023).In addition, AI technologies are utilized in continuous patient monitoring systems to enhance the quality and reliability of care (Jangra & Singh, 2024).

Healthcare Administration: Beyond clinical settings, AI is also proving value by streamlining administrative tasks and improving the overall efficiency of healthcare systems. AI-powered systems can automate routine tasks such as medical documentation and scheduling (Maleki et al., 2024). Furthermore, AI-based chatbots and virtual assistants are deployed to enhance patient engagement, provide personalized healthcare guidance, and improve the overall patient experience (Aggarwal et al., 2023).

While some are thrilled by such news of technological breakthroughs in the healthcare field that has been judged over the decades as short-staffed, many others, including patients, raise concerns about the "black box" nature of AI and believe that AI in itself remains a myth (Akinrinmade et al., 2023; Williamson & Prybutok, 2024).

1. **Patient-AI Interaction in Healthcare Settings**

**A.2.1. General perceptions and awareness of AI among patients**

The rise of AI in healthcare has sparked various responses from patients regarding its potential use and implications. Patients’ general awareness of AI applications in healthcare is often limited, with many individuals lacking a deep understanding of its specific uses beyond broad concepts (Vo et al., 2023). Young et al. (2021) conducted a systematic review of patient perspectives on AI, finding that while participants were generally familiar with AI, they were less familiar with clinical-related AI. Similarly, a systematic review of public opinion surveys in the United States found that, while many Americans are optimistic about the benefits of AI in medicine, there is still significant confusion about its specific roles, such as its use in diagnosis or patient monitoring (Beets et al., 2023). Studies suggest that demographic factors such as age, education level, and technological proficiency may shape awareness. Younger individuals and those with higher education are generally more informed about AI and its potential, whereas older adults and individuals with lower technological literacy exhibit more apprehension and limited understanding (Witkowski et al., 2024).

Patients view AI as a transformative technology, believing it can improve diagnostic accuracy and streamline healthcare processes (Esmaeilzadeh et al., 2021). However, they often struggle to grasp its complexities, particularly regarding personal health applications. A common finding in recent studies is that patients are more comfortable with AI playing a supportive role rather than being the primary decision-maker in treatment (Wu et al., 2023; Witkowski et al., 2024; Lennartz et al., 2021). Despite increasing evidence showing that patients are becoming more open to the use of AI in healthcare, findings vary depending on the surveyed group and the AI tool examined (Fritsch et al., 2022). Moreover, the underlying psychological perceptions and reactions shaping patient experiences while interacting with AI for health purposes are yet to be fully understood.

**A.2.2. Patient-AI Interaction Models**

Human-computer interaction models

Human-computer interaction (HCI) theories primarily focus on cognitive processes and provide a foundation for understanding how patients interact with advanced technologies in healthcare settings. Over the last decade, HCI theories have evolved to include emotional, social, and contextual factors. Frameworks like User Experience (UX) now consider factors such as aesthetics, usability, and emotional satisfaction alongside cognitive efficiency (Bate & Robert, 2023) and emphasize the need to create technology that is not only functional but also emotionally resonant (Yusa et al., 2023). The Cognitive Load Theory (CLT) is applied to health technology interface research and describes the mental load of converting learned information into mental schema. Reducing extraneous cognitive load creates more usable systems by easing the cognitive burden of completing a task (Clarke et al., 2020).

Despite advancements in UX and emotional design frameworks, they do not sufficiently address healthcare-specific emotional responses, such as fear and anxiety, that patients may experience while navigating life-altering decisions with AI-driven tools. In addition, these frameworks are mainly developed for general consumer products or services, focusing on improving user satisfaction; however, they do not consider the underlying psychological themes specific to healthcare (Glikson & Woolley, 2020).

Patients' mental models

The concept of mental models has been explored in the context of patients’ interactions with health technologies. Mental models serve as cognitive frameworks, enabling individuals to interpret their surroundings and anticipate system behaviors (Johnson-Laird, 1989). In the context of healthcare, patients develop mental models of technology based on their previous experiences, general knowledge, and interactions (Barber et al., 2023; Gabbas & Kim, 2022). However, one significant challenge to shaping accurate mental models of AI is the complexity of AI systems. Most patients have a limited or superficial understanding of AI, often associating it with automation or robotics without grasping the more nuanced applications in healthcare, such as AI-driven diagnostics and personalized treatment (Esmaeilzadeh et al., 2021; Vo et al., 2023).

There has been limited work focused on informing human mental models of AI systems (Bansal et al., 2019), but the structure and dynamics of patients' mental models while interacting with AI remain unclear. Understanding the mental models of these systems is becoming increasingly important in the evolving landscape of AI systems in healthcare. An in-depth examination of patients' mental models of AI systems that explores the mechanisms involved will contribute to an advanced comprehensive theory of patient-AI interaction.

Technology acceptance models

Most recent AI-related studies use acceptance models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), to investigate user-AI interactions. TAM, introduced by Davis in 1989, focuses on predicting and explaining user acceptance of new technologies. Its primary focus is on two key factors: perceived usefulness and perceived ease of use. TAM has been widely applied to understand patient acceptance of various healthcare technologies. UTAUT is a more comprehensive model that integrates elements from earlier technology acceptance models, including TAM, and identifies four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, such as organizational and technical infrastructure that exist to support the use of the system (Venkatesh et al., 2003). Holden and Karsh (2010) systematically reviewed TAM applications in healthcare. They found that the model's core constructs of perceived usefulness and ease of use were generally significant predictors of acceptance. Liu et al. (2019) applied the TAM to develop a framework that tested the factors influencing patients’ continuance intention to accept AI-powered service robots at hospitals with intelligent guides. They found that patients’ trust in AI techniques positively influenced their perceptions of usefulness, ease of use, and enjoyment, which were significant predictors of continuance intentions toward AI-powered service robots. UTAUT has also been applied to understand patient acceptance of healthcare technologies. Nakata et al. (2019) applied UTAUT to examine factors influencing the acceptance of AI-powered mental health chatbots. They found that performance expectancy and social influence are particularly important for predicting user acceptance of AI applications.

It must be noted that TAM and UTAUT were not developed within a healthcare setting but were based on studies of e-mail and word processing systems (Venkatesh et al., 2003). Both focus on aspects such as the perceived usefulness of the technology, performance expectations, and ease of use (Sohn & Kwon, 2020). Emotional factors that influence user experience and technology acceptance in healthcare are not effectively covered by TAM and UTAUT. Moreover, previous analyses have shown that these models fail to provide stable findings regarding the acceptance and use of advanced technologies in healthcare (Ammenwerth, 2019; Ward, 2013).

**A.2.3. Psychological Themes in Patient-AI Interactions**

Patient attitudes towards AI in medicine are a topic of growing interest. Patients' attitudes toward AI differ; some are optimistic about its potential to enhance healthcare, while others harbor concerns, especially about possible misdiagnoses and privacy breaches (Khullar et al., 2022). Very few recent studies have explored patient perceptions, acceptance, and expectations regarding the use of AI in healthcare. While most of these studies relied on surveys that are based on well-known HCI or technology acceptance models (such as the TAM and UTAUT mentioned above), few have used qualitative methods to explore attitudes toward the use of AI for a specific medical purpose, such as interpreting radiology imaging data (Zhang et al., 2021), supporting decision-making for heart failure self-management (Zippel-Schultz et al., 2021), and assisting with cardiotocography interpretation in intrapartum care (Dlugatch et al., 2023). The findings of these studies showed that patients expressed varying emotions and perceptions of personal interactions with AI tools, highlighting the need to comprehensively explore the psychological themes involved in patient-AI interactions. Nevertheless, several perceptions and reactions have been studied in relation to patient-AI interactions over the last few years.

Trust, distrust, and perceived autonomy

Trust is fundamental for a functioning health system (Gille et al., 2015) in which patients are vulnerable, because it increases the tolerance to uncertainty and reduces perceived complexity (Luhmann, 2017). Studies focused on trust in AI systems show that patients are likely to exhibit a lack of trust in the features of AI systems, their predictive power, and their diagnostic performance for treatment purposes (Sun & Medaglia, 2019; Esmaeilzadeh et al., 2021; Vo et al., 2023). A recent scoping review found three themes that influenced trust in AI with respect to its implementation in healthcare: individual, AI, and contextual characteristics (Steerling et al., 2023). Individual characteristics, such as gender, age, education (Yakar et al., 2022), knowledge and technological skills (Liu & Tao, 2022), health conditions, and healthcare consumption (Esmaeilzadeh et al., 2021; Yakar et al., 2022), were found to influence trust in AI. In relation to the characteristics of AI, its ability to individualize has been shown to enhance trust (Esmaeilzadeh et al., 2021; Liu & Tao, 2022), while its non-transparent and autonomous characteristics elicited uncertainty and threatened trust (Choi et al., 2020). Regarding contextual characteristics, interpersonal relationships, collaboration, personal interactions, and mutual understanding influence trust (Roski et al., 2021). Thus, reduced communication concerning AI implementation is believed to contribute to lower levels of patient trust (Esmaeilzadeh et al., 2021; Yakar et al., 2022).

Patients may often distrust AI in healthcare, particularly when its role or potential benefits are unclear. Distrust is often rooted in concerns about the accuracy of AI-driven decisions or fears that AI systems could undermine human judgment. Patients who distrust AI are more likely to feel apprehensive or resist its integration into their care, especially when they believe AI could lead to errors or reduce their autonomy in decision-making (Esmaeilzadeh, 2020). (Alanzi et al., 2023). Pesapane et al. (2024) found that patients prefer that AI enhance rather than replace human decision-making in healthcare, which aligns with a preference for maintaining autonomy and control over health decisions. Another recent study that examined factors associated with patient autonomy in AI-mediated healthcare interactions highlighted how perceived privacy risks and ethical concerns can negatively influence patients' perceived control, indicating that a balance between AI assistance and patient decision control is vital.

Theories of trust, distrust, and the link to autonomy in human-AI interactions are still evolving, particularly in healthcare settings where trust is paramount. As AI systems become more autonomous, crucial unknowns and ongoing questions remain, such as how the patient's mental model and perception of AI agency affects trust, or at what point the increased autonomy of AI systems starts to decrease trust among patients. A deeper understanding of the aspects that foster or undermine trust in AI-driven healthcare tools can contribute to theories of trust-building in automated systems, helping to establish future theoretical frameworks for developing AI systems that align with human trust dynamics (Witkowski et al., 2024; Esmaeilzadeh et al., 2021).

Anxiety and fear

Anxiety and fear related to AI use in healthcare have been highlighted recently as significant barriers to its acceptance by patients. Recent studies report the emotional responses of patients, particularly feelings of anxiety and fear due to uncertainty, lack of control, and concerns about depersonalization when interacting with AI-driven healthcare tools (Chew & Achananuparp, 2022; Bekbolatova et al., 2024; Heudel et al., 2024). Anxiety related to patient-AI interactions in healthcare can arise from various sources and affect different aspects of patient experiences and decision-making. Patients are often anxious about how their health data is handled, fearing unauthorized access or misuse. Concerns about data privacy can diminish trust and increase anxiety (Starke & Ienca, 2022; Kerasidou, 2020). Anxiety may also influenced by a perceived lack of personal care and understanding traditionally provided by human care providers (Kerasidou, 2020). Furthermore, the perceived absence of human empathy in AI interactions can generate anxiety, as patients may feel that their unique circumstances and emotions are not adequately addressed (Fazakarley et al., 2024). Additionally, anxiety can stem from the complexity of AI systems and patients' perceived inability to understand how decisions or recommendations are made (Esmaeilzadeh et al., 2021). Hence, when patients feel they must grasp complicated AI algorithms, their cognitive load increases, potentially causing decision fatigue and anxiety (Kersten et al., 2021). Although recent research has made strides toward identifying the sources of anxiety related to interaction with AI for health purposes, significant gaps remain. These include exploring the differences in AI-related anxiety among patient populations, understanding the role of transparency and empathy in decreasing fear of AI, the impact of AI-related anxiety and fear on patients' health decisions, and the association between AI-related anxiety and fear, autonomy, and perceived control.

Comfort and reassurance in patient-AI interactions

Seeking comfort and reassurance during patient-AI interactions in healthcare is a complex psychological phenomenon that intertwines with trust, expectation management, and emotional support. The literature captures several elements relevant to understanding how patients might seek comfort and reassurance from AI in healthcare settings. A recent experimental study found that chatbots expressing sympathy and empathy were perceived as more attractive and competent, thereby enhancing comfort and reassurance for users seeking health advice (Liu & Sundar, 2018). Esmaeilzadeh et al. (2021) have shown that patients often seek reassurance about the accuracy and reliability of AI systems, especially in clinical applications. Research indicates that perceived anthropomorphism, or making AI systems appear more human-like, can enhance comfort by making interactions feel less mechanical and more intuitive (Prakash & Das, 2024). This can include the ability of AI to explain decisions, thereby demystifying its processes and presenting a more relatable interface (Aquilino et al., 2024). Nevertheless, research focused on how personalization interacts with emotional responses and reassurance remains limited. Understanding the influence of patients' mental models pertaining to the empathetic capabilities of AI and managing patient expectations around anthropomorphism require further exploration.

A review of the literature reveals that while research has advanced in the technical implementation of AI in healthcare, there remains a significant gap in the characterization of patients' reactions and perceptions when interacting with these AI tools. The unique context of healthcare, combined with the rapidly evolving nature of AI technology, likely engenders psychological themes and cognitive processes that have yet to be fully identified and understood. While some individual responses (e.g., trust and anxiety) have been studied in relation to health AI, there is no comprehensive theoretical model that integrates these themes to explain patient-AI interaction comprehensively. Moreover, most studies focus on AI’s technical accuracy, operational benefits, and efficiency gains in healthcare but overlook the psychological dimensions of patient experience during interactions with AI tools. Very few recent studies that have examined hypothesized psychological themes of patient-AI interactions, often using traditional models such as TAM and UTAUT, focused on testing the acceptance and usability of a particular AI tool. There is a lack of in-depth qualitative studies that explore the nuanced psychological experiences of patients interacting with AI, which are necessary for building a grounded, comprehensive theoretical model. While past studies provide valuable preliminary insights into patient views on AI in healthcare, more research is needed as AI systems move from concept to reality in clinical practice.

1. **Research Objectives and Expected Significance**

The proposed research effort will explore the underlying themes and meanings patients ascribe to the use of AI tools for health purposes and generate a theoretical model explaining how these themes interrelate and affect patients' experience with AI interaction. This proposed study seeks to use triangulated qualitative methods and interpretative phenomenological analysis (IPA) to understand how individuals make sense of health-related AI interactions (Cronin & Lowes, 2016). The triangulated qualitative research will reveal patients' more profound subjective emotional and cognitive responses toward AI tools, such as trust and distrust, perceptions of autonomy and control, feelings of fear and anxiety, comfort, and reassurance, examine how these responses linked and intertwined with other psychological themes, and understand the structure and dynamic of patients' mental models created while interacting with AI.

The significance of this project stems from its potential contribution to the scientific body of knowledge pertaining to the psychosocial perceptions and reactions involved in human-technology interactions. Moreover, this proposed effort will provide new insights into psychosocial themes relevant to health-related AI interactions among patients; an area in which knowledge remains scarce. Using an IPA approach, this research will develop a foundational understanding of patients' experiences when engaging with AI technology, providing a model that can inform future research and enable subsequent studies to test the model in broader populations or specific AI-driven health contexts.

This project will bridge the gap between existing technology acceptance models and the unique psychological dynamics of patient-AI interaction in healthcare contexts, potentially leading to a novel, health-specific model of human-AI interaction. The proposed theoretical model could inform multiple fields, including health psychology, human-computer interaction, and medical informatics, providing a framework for understanding patient-AI interactions. While primarily theoretical, the model will have future potential practical implications, providing testable hypotheses and themes that can be operationalized, bridging the gap between theory and practice in this rapidly evolving field. In addition, it may lead to paradigm shifts in how we conceptualize patient-AI interactions, potentially revealing new avenues for improving patient outcomes, AI design, and the overall integration of AI into healthcare systems.

1. **Detailed Description of the Proposed Research**

**Working hypothesis**

The current research seeks to construct a theoretical model by developing a deeper understanding of the phenomena and identifying emerging patterns and relationships that may not be fully captured through hypothesis-driven research. Therefore, research questions have instead been formulated to provide the flexibility needed for discovery and theory generation. This approach allows for the open-ended exploration of underlying psychological themes without the constraints of testing predefined assumptions. Accordingly, the overarching research question of the proposed research is as follows:

1. How do patients perceive, make sense of, experience, and react to using AI for health purposes?

The research sub-questions derived from this overarching question are as follows:

1. What are the key underlying psychological themes involved in patient perceptions of health-related AI?
2. How do these themes interrelate and affect patient experience during interaction with health-related AI systems?
3. How do patients’ mental models of AI develop through different types of exposures and interactions?
4. How do patients' emotional reactions, cognitive responses, and perceptions toward AI differ from those toward human healthcare providers?
5. Do different types of diseases and demographic characteristics elicit different emotional and cognitive responses to AI?

**Research Design and Methods**

The proposed research plan will be submitted to the Ashkelon Academic College Ethics Committee. This research employs integrated qualitative methods consisting of initial semi-structured in-depth interviews, scenario-based in-depth interviews, and simulation-based interactions. This triangulated approach will help deepen and enrich data interpretation. The research design will follow a progressive approach, where each phase builds on insights gathered from previous phases. In this approach, the theoretical model will be iteratively developed and refined throughout the research phases. Figure 1 describes the research phases. Detailed descriptions of the tools involved in each phase can be found in the following section of the proposal.

Figure 1: The proposed research phases

**Research Sample and Sampling Method**

This project will involve 50 participants suffering from chronic diseases. Chronic diseases often require the continuous self-management of health conditions while receiving medical services from various healthcare providers, resulting in the use of advanced technologies becoming more prevalent among patients with chronic diseases (Jiang & Cameron, 2020). The general criteria for participation will include patients who are over 18 and are Hebrew speakers, suffering from one of the common chronic physical conditions in Israel, according to previous estimations in Israel (Hayek et al., 2017), including diabetes, migraine, cancer, cardiovascular conditions, and respiratory conditions, and without a diagnosed mental illness. Purposive sampling will ensure diversity in age, gender, socioeconomic status, and health conditions. The proposed sample size of 50 participants is based on the data saturation principle, a key criterion in qualitative research to ensure that the depth and breadth of insights are fully captured. According to Guest et al. (2006), saturation typically occurs within the first 12 to 15 interviews for most themes, with diminishing returns beyond this point. However, given the diversity and variations in age, gender, and health conditions, and considering that the research wishes to identify differences among patients with various types of chronic diseases and demographic characteristics, the proposed sample size will ensure that saturation will be achieved across these different contexts and that all relevant themes will be identified.

Patients will be recruited through advertisements posted in patient-support groups and associations active on social network platforms. Previous research has shown that targeted social networks can substantially aid participant recruitment (Khatri et al., 2015). A recent review showed that social network platforms served as efficient and effective venues for recruiting young as well as mid-life and older patients for clinical trials (Reuter, 2020). For example, Wisk et al. (2019) used social network platforms and recruited 227 college students with Type 1 diabetes mellitus for an online longitudinal intervention trial. Langbaum et al. (2019) were able to enroll, using social network platforms, 75,351 adults aged 55–75 years in the USA into a registry of Alzheimer’s disease prevention studies online.

A preliminary investigation of social networks revealed that there are currently four Israeli public support groups for diabetes patients, including 30,300 members; four Israeli public support groups for patients who have asthma or other respiratory conditions, including 24,000 members; two Israeli public support groups for patients suffering from cancer (general support groups and not cancer-specific) including 3,200 members; and three Israeli public support groups for patients suffering from cardiovascular conditions including 3,500 members. Advertisements will include a description of the study aims and procedures. Patients who contact the researcher will receive detailed information about the research effort and will be asked to participate in all four phases of the study. Participants will also be informed that participation is voluntary and can be withdrawn at any time without consequences and that they will receive a 150 NIS gift voucher for participation in each research phase. A research assistant will schedule meetings with the participants at a time and place convenient for them. Each participant will be asked to sign an informed consent form approving participation, recording of the interviews, and transcription.

**Tools**

1. **In-depth interview:** A Semi-structured initial explorative interview guide was developed based on a literature review regarding patients' perceptions, emotions, mental models, and attitudes toward using AI technologies in health-related contexts. The guide includes 13 open-ended questions and will be modified and refined through the pilot phase of the research to examine patients' reactions and perceptions related explicitly to AI technology. The pilot phase will include 5 participants. Each interview will last 45 minutes and will be recorded and transcribed. The findings from the interviews will assist in the refinement of scenarios to be used in the following phases. Table 1 presents the interview guide.

**Table 1: Interview Guide**

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| **Section** | **Questions** |
| Section 1: Introduction and Background | "Can you tell me about your health condition? Describe your interaction with health professionals." |
|  | "Can you tell me about your experience with AI or technology in healthcare?  |
|  | "How familiar are you with AI's use in healthcare? What do you think AI can do in this context?" |
| Section 2: Trust in AI | "If you were to receive medical advice or a diagnosis from an AI system, how would you feel about trusting that information? Would you trust it as much as advice from a human healthcare professional?" |
|  | "How important is it to you that a doctor reviews the AI’s recommendation before you make any decisions? Would you feel more comfortable if a doctor and the AI worked together?" |
| Section 3: Perceived Control and Autonomy | "When you think about using AI for your health condition, do you feel you would still have control over your health? Why or why not?" |
|  | "How would you feel if an AI system made decisions about your treatment plan with limited involvement from your doctor? Does that idea affect how much control you feel you would have?" |
| Section 4: Anxiety and Fear | "What worries, if any, about AI being used in healthcare? For example, are you concerned about the accuracy of its recommendations, the privacy of your data, or losing the human connection in your care?" |
| Section 5: Emotional Responses | "Would you feel comfortable using AI as part of your healthcare treatment? What might help you feel more at ease with AI systems in healthcare?" |
|  | "If an AI system made a serious diagnosis or treatment recommendation, how would that affect you emotionally? Would you feel reassured by the AI's data-driven decision, or would you feel anxious?" |
| Section 6: Experience and Recommendations | "Have you had any experiences where technology played a big role in your health? How did that experience make you feel? Was it positive or negative?" |
|  | "What do you think healthcare providers or developers could do to make AI systems more comfortable or trustworthy for patients like you? What improvements could be made?" |
| Section 7: Closing | "Is there anything else you want to share about how AI might impact your healthcare experience?" |

1. **Vignette technique:** Vignette research methodology uses hypothetical but realistic narrative-like descriptions of situations to explore the decisions, beliefs, and attitudes of the respondents (McDonald, 2019). This tool enables moving beyond abstract perceptions of AI to investigate how patients’ psychological reactions manifest in specific health scenarios. Five vignettes were designed to elicit reactions and opinions toward real-life contexts of using AI for health purposes. Nevertheless, using emergent themes from earlier phases, the vignettes will be refined and tailored to reflect real-world concerns about interactions with AI. Each participant will be presented with two of the five developed vignettes and asked to describe thoughts, feelings, and concerns regarding the described health-related AI applications, providing a more nuanced view of how patients might respond to AI-driven decisions. Table 2 presents these vignettes.

**Table 2: Vignettes**

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| Vignette 1: AI-Assisted Diagnosis: A 45-year-old patient visits a clinic with persistent symptoms of a skin rash. After an initial consultation, the doctor informs the patient that an AI system will analyze their medical history, symptoms, and test results to recommend a diagnosis. The AI system's recommendation is provided directly to the patients, who may then ask the doctor to explain the results. |
| Vignette 2: Autonomous AI Treatment Recommendation: A 50-year-old patient has been diagnosed with an inflammatory bawl disease. The doctor suggests using an AI system to recommend the best treatment based on previous successful cases. The system will select a treatment and explain why it is optimal, though the doctor will have the final say. The patient is given the option to accept or reject the AI's recommendation. |
| Vignette 3: AI Monitoring in Post-Surgery Recovery: A 40-year-old patient has recently undergone surgery and is recovering at home. The doctor informs the patient that an AI system will remotely monitor their vital signs, medication adherence, and recovery progress. The AI will alert the doctor to any abnormalities, but the patient is not required to visit the clinic unless the AI detects an issue. |
| Vignette 4: AI-Generated Prognosis: A 25-year-old patient is informed that an AI system will provide a prognosis for their illness based on their medical data. The AI-generated prognosis is presented alongside the doctor’s interpretation, and the patient is asked to consider both when making decisions about their treatment. |
| Vignette 5: AI in End-of-Life Care: A 35-year-old patient with a terminal illness is offered an AI tool that can predict their life expectancy based on various health factors. The AI prediction is presented as an aid for the patient to make informed decisions about their remaining time, such as whether to pursue aggressive treatment or focus on palliative care. |

1. **Simulationstechnique:** Simulation will involve exposing participants to actual AI interactions and directly observing how they respond emotionally and cognitively to AI tools in real time. As previously mentioned in the scientific background (A.2.1.), patients still have significant confusion about AI-specific roles, such as its use for diagnosis or patient monitoring. Therefore, the simulation technique will include patient-driven interactions in which participants will be encouraged to interact with an AI-based technology, the Claude 3 Haiku generative AI, which allows dialogs in Hebrew. Before the simulations, participants will be explicitly informed about the nature of the AI system they will interact with. The simulated interaction with the system will be based on vignettes 1 and 2 from the earlier phase (see Table 2), where participants will input hypothetical medical information according to the described vignette, receive AI-generated feedback, and respond to prompts (e.g., hypothetically accepting a diagnosis or selecting a treatment based on AI recommendations). During the simulation, participants will be guided not to input any personal medical information. Participants will be asked to “think aloud” and describe their thoughts and feelings throughout the interaction. The interactions will be recorded to track how participants respond to AI recommendations and make decisions. Observations of non-verbal behaviors (e.g., hesitation, facial expressions, body language) and verbal reactions (e.g., comments of discomfort, distrust, or confusion) will be collected manually during the interaction. Although recent research has shown that Anthropic’s Claude generative AI includes rigorous safeguards to prevent the generation of health disinformation in stark contrast with other examined AIs (Menz et al., 2024), participants in the proposed study will be provided with a detailed explanation of the risks and biases involved in AI-based advising for health purposes, and any misconceptions about AI capabilities will be clarified.
2. **Member checks:** This tool will involve presenting the participant with the theoretical model and its themes and conducting repeated interviews to ensure the developed theoretical model resonates with their experiences. Employing member checks for interpretive validity will allow participants to contextualize their previous utterances and affirm or challenge the conclusions made about the collected data. This collaborative approach ensures that the research captures as comprehensive a picture of the participants' worldviews as possible and assists with producing more robust research findings (Coleman, 2022).

**Data analyses**

Data analysis, including the recordings of the simulations, will be conducted using IPA to develop in-depth themes and sub-themes (Smith et al., 2021), focusing on the psychological dimensions of patient interactions with AI. An ongoing internal quality audit will be adapted from Mays and Pope (2000) and Tong et al. (2007) to determine whether the data are collected, analyzed, and reported consistently according to the research protocol. The data collected will be anonymously coded in a file protected by a login password.

Interviews at all phases of the project will be transcribed, and transcriptions will be analyzed using the ATLAS.ti software for qualitative analysis. The analysis of the interviews will include 1) transcribing the interviews, 2) reading and re-reading transcriptions, 3) a detailed, line-by-line coding process to identify codes that emerge from the data, grouping codes into broader themes that explain the central phenomenon, 4) repeating the re-reading and coding stages, 5) comparing and refining themes, 6) identifying superordinate themes, and 7) interpreting the findings.

The analysis of the simulations will entail the following: 1) participants’ verbal reactions during the simulation (captured by audio) will be transcribed and analyzed to identify cognitive and emotional language and sentiment; 2) identification and coding of recurring themes related to participants' experience of the AI system for example, critical moments of hesitation, frustration, or reassurance will be coded as specific instances where psychosocial factors (e.g., trust, autonomy) are visibly at play; 3) non-verbal behaviors such as body language and facial expressions will be coded into categories such as positive (e.g., nodding, smiling) or negative (e.g., frowning, avoiding eye contact) reactions to the AI interaction.

The data from each phase will be continuously analyzed and integrated into the subsequent phase, creating a feedback loop that refines and deepens the understanding of psychosocial themes at each stage. This integrative approach will help validate the findings and provide a multidimensional understanding of how perceptions and reactions evolve. The final theoretical model will illustrate the relationships between themes and patients' experiences and meaning-making associated with using AI in the health context.

**Expected Results**

Expected results will include several working outcomes which will present the interim findings of the research phases and the final theoretical model of the psychological themes in patient-AI interactions, including:

1. The initially planned publication of four scientific articles in high-rated journals to present: A) Findings from the in-depth interview phase, B) Findings from the vignette-based interview phase, C) Findings from the simulation-based interview phase, and D) Cross-phase analyses and the finalized theoretical model.
2. The findings from the different phases of this research effort will be prepared for presentation at various scientific conferences related to health psychology and health technologies during the research period.
3. A report presenting summaries of the research findings and detailed recommendations will be translated into English and shared with national and international healthcare organizations, health-related AI developers, and health policymakers.
4. A summary of the research findings and recommendations will be published on patient advocacy websites and presented to patients’ organizations.

 **Expected Pitfalls**

1. Difficulty recruiting patients to participate in the research: To overcome this challenge, patients will be fully briefed about the research procedures and the maintenance of participant anonymity. In addition, Participants will be informed that their participation is voluntary and can be withdrawn at any time without consequences and that they will receive a 150 NIS gift voucher for participation in each of the research phases. Offering incentives to participants may help overcome recruitment challenges.
2. Participant sample bias: Using social networks for participant recruitment may introduce a selection bias, as participants recruited through these platforms are likely to have higher digital literacy compared to the general patient population. However, recent reviews found significant concerns and distrust toward AI in healthcare, even among technologically engaged populations (Wu et al., 2023; Young et al., 2021). Nevertheless, to mitigate this bias, the data collection process will be examined in several intermediate stages throughout the study in order to examine whether it fails to capture the experiences and concerns of patients who are less comfortable with technology. If that is the case, recruitment efforts will be diversified by adding snowball sampling to ask participants to refer others who may be less active on social media.
3. Dropout during the research: Long-term studies among patients report a typical 10% – 30% dropout, depending on the participant's commitment level and the research length (Mantovani et al., 2010). Therefore, to deal with dropouts, the researcher will maximize the initial number of participants, assuming that a dropout rate of 20% of the participants is to be expected during the research period.

**Conditions Available for Conducting the Research**

The researcher is an expert in human factors engineering in health, patient-centered design, user-experience research in health settings, digital health, and patient safety. As listed in the researcher list of publications submitted with the research proposal, more than 20 scientific articles presenting research findings related to these topics have been published by the researcher in various international journals, including the *European Journal of Investigation in Health Psychology and Education*, *Healthcare, Journal of Patient Safety*, *PLOS One,* and *Frontiers in Public Health*. The researcher has administrative services provided by the institutional research authority, access to a simulation center, and other research infrastructure available through her academic affiliations with the Ashkelon Academic College. In addition, the researcher is also a research fellow at Ben-Gurion University of the Negev, where she supervises Master’s students and has working relationships with experts in the field. The researcher is also active in current research projects with several health organizations, among them: A) Maccabi Health Services, investigating patient experience with an innovative digital application for remote emergency care; B) Shaare Zedek Medical Center, investigating the cancer patient journey; and C) Barzilai Medical Center, investigating the applications of innovative intervention to prevent patient falls. These collaborations will assist the researcher in conducting the proposed research.

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