

**MINISTRY OF EDUCATION AND TRAINING
NATIONAL ECONOMICS UNIVERSITY**



DAO MINH HOANG

**DETERMINANTS OF INTENTION TO USE
ARTIFICIAL INTELLIGENCE IN HEALTHCARE:
AN EMPIRICAL STUDY IN VIETNAM**

**PHD DISSERTATION
IN BUSINESS ADMINISTRATION**

HANOI - 2026

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(E-PHD Program)**

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PHD DISSERTATION

***Supervisors:* Prof. Dr. NGUYEN THI TUYET MAI**

HANOI - 2026

DECLARATION

I hereby declare that this PhD dissertation is my work. To the best of my knowledge, this dissertation has never been submitted, in whole or in part, to any other educational institution for a degree or a diploma. Except where specified otherwise by acknowledgment or reference, the work presented is entirely my own. I also certify that all of this PhD dissertation's references have been properly credited.

I have read and comprehended the University's policy on plagiarism and academic integrity violations. With my honor, I certify that the current PhD dissertation does not violate regulations on academic integrity.

PhD candidate

Dao Minh Hoang

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LIST OF ABBREVIATIONS

Abbreviations	Full form
AI	Artificial intelligence
AIDUA	Artificially intelligent device use acceptance
AIMDSS	Artificial intelligence medical decision support system
ANOVA	Analysis of variance
ANTH	Anthropocentrism
ATT	Attitude
BRT	Behavioral reasoning theory
CRM	Customer relationship management
HIT	Health information system
INT	Intention
IT	Initial trust
ITH	Identity threat
LMIC	Low – and middle-income countries
MANCOVA	Multivariate analysis of covariance
MS	Modern self
PBC	Perceived behavioral control
PIHT	Personal innovativeness in domain of health technology
RTH	Realistic threat
SEM	Structural equation modeling
SN	Subjective norm
TAM	Technology acceptance model

Abbreviations	Full form
TO	Technology optimism
TPB	Theory of planned behavior
TRA	Theory of reasoned action
TS	Traditional self
UTAUT	Unified theory of acceptance and use of technology
VAB	Value-attitude-behavior model

INTRODUCTION

1. Rationale of the research

Vietnam, with a population exceeding 100 million, is undergoing rapid economic and demographic transitions that directly shape its healthcare needs. The country has sustained robust economic growth, averaging nearly 7% in recent years, with GDP per capita estimated at USD 4,806 in 2025, reflecting both rising purchasing power and an expanding middle class (World Bank, 2024). While Vietnam is currently benefiting from a “golden population structure” with a large working-age cohort, fertility rates have declined below the replacement level (1.91 children per woman in 2024; 1.39 in Ho Chi Minh City), and the country is projected to enter an “aged society” by 2035, raising concerns about future healthcare demand (Le, 2025). At the same time, the healthcare system remains under strain: with only 11.07 physicians per 10,000 population, among the lowest in the region, Vietnam faces high patient-to-doctor ratios, clinician burnout, and risks of compromised diagnostic accuracy (World Health Organization, 2022). These pressures coincide with the country’s rising digital readiness, with over 70% internet penetration, near-universal smartphone use, and substantial improvements in national digital infrastructure, making the population increasingly receptive to digital health solutions (Chuc and Anh, 2023; Ministry of Science and Technology, 2024; Vu and Nguyen, 2024). With an estimated 13 million middle-class consumers driving demand for modern healthcare, Vietnam represents a particularly promising market for AI-enabled health innovations (Flanders Investment & Trade, 2023).

Globally, AI applications now span a wide range of consumer touchpoints, including personalized recommendations, virtual assistants, automated decision-making, and predictive analytics, fundamentally transforming how consumers interact with products and services (Davenport *et al.*, 2020). AI technologies have been widely adopted across diverse sectors, including healthcare, finance, retail, education, and transportation, where they support tasks such as diagnostics, fraud detection, customer engagement, personalized learning, and autonomous driving (Davenport *et al.*, 2020; Dwivedi *et al.*, 2021; Kelly, Kaye and Oviedo-Trespalacios, 2023). Unlike other sectors, healthcare is one of the most promising yet challenging domain for artificial intelligence (AI). In other sectors, AI is mainly leveraged to improve efficiency or reduce costs, and at most, what is at risk are the economic or business outcomes. Meanwhile, in the healthcare sector, the stakes are considerably higher, as decisions directly affect human lives and wellbeing (Topol, 2019). AI applications already span diagnostic imaging, predictive analytics for disease outbreaks, personalized treatment planning, robotic-assisted surgery, and administrative process automation (Davenport and Kalakota, 2019). These innovations can reduce medical errors, enhance accuracy, and alleviate inefficiencies, especially in under-resourced systems such as those in many developing countries (Khanijahani *et al.*, 2022; Li and Wang, 2024; Roppelt, Kanbach and Kraus, 2024). The urgency of such solutions is heightened by mounting global challenges, including escalating healthcare costs, ageing populations, increasing prevalence of chronic diseases, and the unequal distribution of medical resources (World Health Organization, 2024, 2025).

In contrast to the extensive body of research on AI adoption in developed countries, studies from developing countries, aside from China, are still comparatively limited (Kelly, Kaye and Oviedo-Trespalacios, 2023; Jain, Wadhwani and Eastman, 2024). Studying developing countries is essential because the conditions that shape medical-AI adoption (e.g., workforce shortages, uneven digital maturity, data-sharing barriers, and differing trust and risk perceptions) often diverge markedly from those in high-income settings. Without specific evidences from Low- and Middle-Income Countries (LMIC), adoption models risk poor external validity and may exacerbate inequities rather than close them (World Health Organization, 2021; Ciecierski-Holmes *et al.*, 2022; Kaushik *et al.*, 2025). In LMIC health systems, AI is frequently framed as a “leapfrog” technology to extend scarce clinical capacity and optimize workflows, but systematic reviews stress that benefits depend on fit with local infrastructure, governance, and public attitudes, which are context-sensitive (Young *et al.*, 2021; Ciecierski-Holmes

et al., 2022). Vietnam represents a particularly salient case, as it combines relatively strong digital readiness, with internet penetration reaching approximately 79 percent in 2025, and an active national digital health agenda, while hospital digital maturity and AI implementation remain nascent and uneven, especially outside major urban centers. (Vuong *et al.*, 2019; Tran *et al.*, 2022; Ministry of Science and Technology, 2024). At the same time, Vietnam faces demographic ageing and persistent workforce constraints, prompting government targets to raise physician density (e.g., to 15 per 10,000 by 2025), underscoring demand-side pressure for scalable digital solutions (Nguyen, 2024). These features make Vietnam an informative LMIC setting for studying the determinants of consumers' medical AI adoption intention. Furthermore, in transitional economies such as Vietnam and China, multiple value systems can coexist within the same individual due to sustained exposure to foreign cultural influences (Zhang and Shavitt, 2003; Nguyen, Smith and Cao, 2009). In this context, self-concept is a salient, context-specific factor because attitudes and intentions to adopt novel technologies, such as medical AI, may be embraced by consumers oriented toward a modern self but resisted by those oriented toward a traditional self.

Despite the potential of medical AI, the adoption of such systems remains modest, particularly among consumers (Frank *et al.*, 2021; Yang, Ngai and Wang, 2024). AI adoption by consumers in general, including in the healthcare sector, faces unique barriers rooted in psychological factors (Longoni, Bonezzi and Morewedge, 2019; Dwivedi *et al.*, 2021; Young *et al.*, 2021). Studies on consumer adoption of AI have revealed inconsistent findings, with some consumers demonstrating receptiveness while others showing resistance. Few have suggested that consumers intend to adopt AI when trust, perceived performance, perceived usefulness, and emotional engagement are strong (Ye *et al.*, 2019; Chatterjee *et al.*, 2021; Ma and Huo, 2023). Also, consumers showed higher acceptance of AI-based advisors when they interacted in a human-like conversational style (Hildebrand and Bergner, 2021). Notably, the study of Logg *et al.* (2019) found that consumers preferred AI system over human in domains of forecasting and personal decision-making. However, resistance to adopt AI due to algorithmic aversion, or fears that AI neglects individual uniqueness has also been reported (Dietvorst, Simmons and Massey, 2015; Castelo, Bos and Lehmann, 2019; Longoni, Bonezzi and Morewedge, 2019). In healthcare, patients often express reluctance to adopt AI-driven services due to a lack of trust, concerns about privacy and data security, and the fear of replacement of human judgment by machine intelligence (Longoni, Bonezzi

and Morewedge, 2019). Further, Young (2021) synthesizes 23 studies and concludes that, although patients and the public are broadly positive about clinical AI, they hold persistent reservations and prefer human supervision. The preference for a human doctor signals psychological barriers tied to trust, perceived loss of the “human touch,” and anxiety about errors. They also highlight that attitudes are context-dependent, shaped by how AI is framed and by local expectations of care. Building on this, von Walter et al. (2022) show that consumers’ lay beliefs about AI (e.g., believing AI is more intelligent than humans) predict adoption of algorithmic advice, particularly on complex tasks. This is a clear demonstration that beliefs act as heuristics guiding acceptance (von Walter, Kremmel and Jäger, 2022). Early “AI-in-service” work largely emphasised capability and task–technology fit, while calling for deeper psychological antecedents, leaving the beliefs pathway comparatively underdeveloped (Huang and Rust, 2018). In healthcare and other sensitive domains, task type and role also interact with beliefs: people are more willing to accept algorithms in objective or routinised tasks than in interpretive or personal roles, reflecting anthropocentric preferences for human agency in “human” roles (Nass *et al.*, 1995; Castelo, Bos and Lehmann, 2019). Together, these findings motivate research on specific beliefs, for example, anthropocentrism (the belief in human dominance and central role) and techno-optimism (a general conviction that technology improves control, efficiency, and outcomes). Empirically, optimism about technology is predictive of adoption across many technologies: a large meta-analysis of Technology Readiness (TR) finds the optimism dimension a robust antecedent of technology use; healthcare reviews likewise report positive effects of optimism on telehealth acceptance (e.g., multi-country evidence where optimism significantly predicts use) (Blut and Wang, 2020). Nonetheless, research on the impact of specific beliefs and the cognitive mechanism via which beliefs influence behavioral intention of consumers is often overlooked by conventional theories (e.g. Theory of Planned Behavior, Social Cognitive Theory)(Granados Samayoa and Albarracín, 2025). Drawing on the taxonomy of beliefs and the concept of belief-to-behavior inference (reasoning process that connects beliefs to behaviors) proposed by Samayoa and Albarracín (2025), this dissertation aims to unveil the role of anthropocentrism and techno-optimism in medical AI adoption of consumers by adopting Behavioral Reasoning Theory. This is a model that Westaby (2005; 2025) considered as most suitable to study these issues.

For the above reasons, it is critical to investigate medical AI adoption, specifically factors driving intention to use medical AI of consumers in Vietnam. Therefore, the author decided to work on the research topic ‘**Determinants of intention to use artificial intelligence in healthcare: an empirical study in Vietnam**’. This dissertation enriches the understanding of psychosocial factors that shape consumers’ intention to adopt medical AI in a developing country, such as Vietnam. Studying the impact of beliefs, the context-specific reasons, and the cognitive mechanisms that connect beliefs to behavioral intention also contribute to the theoretical understanding of the belief-to-behavior-inference, which Samayoa and Albarracín (2025) proposed. These findings provide a basis for actionable strategies in product design, user communication, and onboarding for healthcare providers and medical AI developers, and offer practical guidance to support the responsible and effective diffusion of medical AI in similar settings. In this dissertation, the terms “use” and “adoption” of medical AI are used interchangeably.

2. Research objectives, subjects, and scope of the research

Research objectives

The general objective of this dissertation is to examine consumers’ intention to adopt artificial intelligence in healthcare in Vietnam, with a particular focus on the current level of adoption intention, the key psychosocial factors shaping this intention, and the practical implications for healthcare providers, technology developers, and policymakers. Following that, the specific objectives of this dissertation are as follows:

1. To assess the current state of consumers’ intention to adopt artificial intelligence in healthcare in the Vietnamese context.
2. To identify key psychosocial factors influencing consumers’ intention to adopt healthcare AI, drawing on a belief-based theoretical framework.
3. To examine the effects of these psychosocial factors on consumers’ adoption intention toward AI-based healthcare services.
4. To derive practical managerial and policy implications for stakeholders involved in the development, deployment, and governance of healthcare AI in developing economies.

Research subjects

The research subjects of this dissertation are the determinants of consumers' intention to adopt medical artificial intelligence.

Scope of the research

Research context: This dissertation examines the factors influencing consumers' intention to adopt artificial intelligence technologies in healthcare.

Scope of content: This dissertation investigates the beliefs and relevant reasoning factors that influence consumers' intention to adopt medical AI, specifically Artificial Intelligence Medical Decision Support Systems (AIMDSS). AIMDSS is among the most widely used medical AI systems currently used in healthcare for diagnostic support.

Research space: This dissertation is situated in the healthcare context of a developing country, with Vietnam serving as a representative case.

Research period: Primary data (qualitative and survey data) was collected from 2022 to 2024.

3. Research questions

Prior research has predominantly focused on technological and functional attributes of AI; less attention has been paid to the broader sociocultural context and individual-level perceptions that may facilitate or hinder AI adoption, especially in developing countries. By investigating these understudied dimensions, the study contributes to a more holistic understanding of AI adoption in healthcare. Following that, this dissertation aims to address two research questions:

Research question 1: What belief factors influence the intention to adopt AI in the healthcare context?

Research question 2: How do these beliefs impact the intention to adopt AI in the healthcare context?

4. Research methodology

To comprehensively examine the determinants of consumer adoption intention of artificial intelligence (AI) in healthcare, this dissertation adopts a mixed-methods research design. A combination of qualitative and quantitative approaches is employed to enhance the depth, contextual relevance, and generalizability of the findings. This design is particularly appropriate given the complexity of the phenomenon under

investigation, which involves not only rational decision-making but also belief systems and other psychological factors.

The qualitative component aims to explore consumers' underlying beliefs, reasons, and perceptions surrounding AI in healthcare. This phase involves semi-structured interviews with a diverse sample of informants, including doctors, policymakers, medical AI developers, and consumers across urban and rural areas in Vietnam, and focus group discussions with participants recruited from a university in Hanoi. The purposive sampling strategy ensures variation in demographic characteristics, digital literacy, and healthcare experience. Focus groups help identify common reasoning patterns and cultural attitudes, while interviews allow deeper exploration of individual experiences and psychosocial drivers of adoption or resistance.

Insights from the qualitative phase help elicit factors and specify hypotheses for the quantitative phase. The quantitative study was conducted to test the conceptual model and hypotheses derived from the literature and qualitative findings.

Data were collected from consumers in Vietnam via both offline (paper-based) and online (web-based) survey distribution to maximize reach and representativeness. The study employed partial least squares structural equation modeling (PLS-SEM), using SmartPLS for data analysis. The detailed description of the research methodology used in this dissertation is presented in Chapter 2.

5. Contributions of the research

This dissertation makes several important theoretical contributions to understanding consumer adoption of medical AI, specifically AIMDSS. First, it extends Behavioral Reasoning Theory (BRT) by foregrounding the role of coexisting beliefs in shaping adoption intentions, thereby addressing a limitation of prior studies, which typically examine single beliefs and assume unidirectional reasoning effects. By examining techno-optimism and anthropocentrism simultaneously, the study demonstrates that beliefs can concurrently activate both supportive and opposing reasons for adoption, capturing consumers' cognitive ambivalence toward medical AI. The validated serial mediation mechanism (belief → reason → attitude → intention) further clarifies how abstract, distal beliefs are translated into behavioral intentions through context-specific reasoning processes, thereby advancing belief-to-behavior inference in technology adoption research. Second, the study contributes to the medical

AI adoption literature by identifying a context-specific configuration of reasons for and against adoption in the Vietnamese healthcare context, where initial trust, personal innovativeness in the domain of health technology, and modern self function as key drivers, while perceived threats and traditional self serve as major sources of resistance. These findings reinforce the importance of trust, introduce personal innovativeness in the domain of health technology as a distinct determinant, and highlight the role of sociocultural identity in shaping consumer responses to medical AI. Finally, the study advances understanding of anthropocentrism by revealing its context-sensitive ambivalence: rather than operating solely as a barrier, anthropocentric beliefs can both facilitate and hinder adoption depending on whether AI is framed as human-enhancing or human-replacing, thereby extending existing consumer behavior literature beyond a unidimensional view of anthropocentrism.

From a practical perspective, the dissertation offers implications for healthcare providers, medical AI developers, and policymakers, thereby promoting wider adoption of medical AI among consumers and supporting the successful implementation of this technology in Vietnam.

6. Structure of the dissertation

This dissertation includes four chapters, as follows:

Chapter 1: Literature review and hypotheses development. In this chapter, the author reviews key concepts such as artificial intelligence, AI adoption, and existing research on AI adoption in diverse contexts, including healthcare. The theoretical background and theoretical framework are also presented.

Chapter 2: Research methodology. In this chapter, the author presents the research methodology, including sampling methods, data collection procedures, and research analysis techniques.

Chapter 3: Research findings. In this chapter, the author presents the results of both qualitative and quantitative research. The quantitative results include reliability testing of measurement scales, model assessment for both level constructs, hypothesis testing results, and model fit assessment.

Chapter 4: Discussion and implications. In this chapter, the author discusses the research results and presents both theoretical and policy implications. The author also discusses the dissertation's contributions and limitations and suggests future research.

CHAPTER 1: LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

1.1. Literature review

1.1.1. Overview of AI and AI in healthcare

1.1.1.1. Definition of AI

Artificial Intelligence (AI) has been conceptualized in diverse ways across disciplines, reflecting its multifaceted nature and wide-ranging applications, as summarized in Table 1.1. In the literature, artificial intelligence (AI) is defined using two distinct but complementary perspectives. Some scholars conceptualize AI as a scientific field or application domain, referring to the study, design, and use of computational techniques that aim to replicate or simulate intelligent behavior. From this perspective, AI is framed as a discipline or body of methods focused on modeling intelligence as computational processes (Minsky, 1988; McCarthy, 2007; Russell and Norvig, 2016; Dwivedi *et al.*, 2021). Meanwhile, some scholars define AI as a machine, system, or artifact, emphasizing the observable capabilities of AI-enabled systems. In this view, AI refers to computational systems that can perceive their environment, learn from data, reason, and act autonomously to achieve specific goals, often performing tasks that would otherwise require human intelligence (European Commission, 2018; Haenlein and Kaplan, 2019; Topol, 2019; Huang and Rust, 2021a). In applied domains such as healthcare, the latter definition of AI is more commonly used (Topol, 2019; Khanijahani *et al.*, 2022). Thus, this dissertation adopts this definition of AI.

Table 1.1. Review of AI definitions

No.	Definition	Author (Year)
1	AI involves using computer systems to replicate human-like capabilities, including physical actions, cognitive processing, and emotional responses.	Huang & Rust (2021a)
2	AI is a discipline that seeks to understand and replicate intelligent behaviors by modeling them as computational processes.	Russell & Norvig (2016)
3	AI systems demonstrate intelligent behavior by perceiving their environment and independently making decisions to fulfill defined objectives.	European Commission (2018)
4	AI is the science of enabling machines to execute tasks that would demand intelligence if done by humans.	Minsky (1988)

No.	Definition	Author (Year)
5	AI refers to systems that can correctly process external information, learn from it, and adapt their actions to achieve specific goals.	Kaplan & Haenlein (2019)
6	AI includes a variety of methods allowing computers to mimic intelligent actions, such as learning, reasoning, and self-correction.	Dwivedi et al. (2021)
7	AI generally describes machines that perform human-like cognitive tasks, such as recognizing images, making decisions, translating languages, or understanding speech.	Topol (2019)
8	“The science and engineering of making intelligent machines, especially intelligent computer programs”	McCarthy (2007)
9	AI is a broad category of technologies designed to automate business processes, gain insights from data, or engage customers and employees.	Davenport & Ronanki (2018)

1.1.1.2. Classification of AI

Artificial Intelligence (AI) can be classified in multiple ways depending on its capabilities, functions, embodiment, and application contexts. A widely used classification based on capability distinguishes three levels: narrow (weak) AI, which excels at specific tasks like image recognition or language translation; general AI, which hypothetically possesses versatile, human-like cognitive abilities; and superintelligent AI, which would outperform humans across virtually all domains (Goertzel and Pennachin, 2007; Bostrom, 2014; Russell and Norvig, 2016; Haenlein and Kaplan, 2019). These categories highlight the evolving complexity of AI while framing it within both current capabilities and future aspirations.

Another classification method focuses on functionality, distinguishing AI into reactive machines, limited memory systems, theory of mind AI, and self-aware AI (IBM, 2023). Reactive machines respond to specific inputs with pre-programmed outputs without memory or learning capabilities. Limited memory systems, such as AI in autonomous vehicles or medical diagnostics, can learn from historical data to inform future decisions. Theory-of-mind AI, still under development, aims to understand human emotions and intentions. In contrast, self-aware AI, representing the most advanced stage, would possess consciousness and self-perception, though it remains hypothetical.

Complementing this capability-based view, Glikson and Woolley (2020) propose an embodiment-based classification that is particularly relevant to user perceptions and trust. They differentiate AI systems by their physical manifestation: physical (robotic) AI, such as service or industrial robots; virtual AI, such as chatbots and virtual agents; and embedded AI, which operates invisibly within tools or platforms. Their meta-analysis emphasizes how embodiment, whether AI is tangibly present, graphically visible, or unobtrusively integrated, affects trust development, with physical and virtual forms often eliciting greater emotional engagement than embedded systems.

1.1.1.3. AI in healthcare

Given the rapid advances in AI in recent years, it has become an increasingly integral component of healthcare innovation, offering substantial improvements in accuracy, efficiency, and personalization across a wide range of medical domains. In healthcare, most implemented AI technologies fall under the category of narrow AI. These include a diverse array of applications such as AI-powered chatbots, robotic surgical systems, embedded AI in wearable health devices, and anthropomorphic healthcare robots designed to enhance patient interaction (Topol, 2019; Khanijahani *et al.*, 2022). Thus, to study the determinants of consumers' intention to adopt AI in healthcare, it is essential to understand the concept of AI and its applications in healthcare.

Definition of AI in healthcare/ medical AI

In the medical context, Artificial Intelligence (AI) in healthcare, or medical AI, refers to the technological systems capable of processing and analyzing data, making decisions, and assisting healthcare professionals by simulating human cognitive abilities (Khanijahani *et al.*, 2022). The use of this system has reportedly been increasing in both developed and developing healthcare settings (Prakash and Das, 2021; Khanijahani *et al.*, 2022; Li and Wang, 2024).

Application of medical AI

AI applications in healthcare can be broadly categorized into diagnostic support, treatment planning, patient engagement, operational management, and drug discovery (Khanijahani *et al.*, 2022; Roppelt, Kanbach and Kraus, 2024). Among AI applications in healthcare, robotic surgery represents a frontier where AI is applied to enhance surgical precision, reduce variability, and enable minimally invasive procedures. AI-powered robotic systems can assist in preoperative planning and intraoperative navigation, improving patient outcomes and recovery times (Hashimoto *et al.*, 2018). In patient-facing applications, AI chatbots and virtual health assistants are being used to

facilitate appointment scheduling, triage symptoms, remind patients of medication, and provide health education. These systems can improve patient engagement, particularly in settings where access to medical personnel is limited (Nadarzynski *et al.*, 2019; Kurniawan *et al.*, 2024). Embedded AI in wearable health devices and remote monitoring systems further enables real-time data collection and health tracking, supporting preventive care and chronic disease management. These tools are especially beneficial for managing conditions such as diabetes, hypertension, and heart disease, offering patients and providers timely insights and alerts (Zeng, Cao and Neill, 2021; Shaik *et al.*, 2023). Moreover, AI has shown significant promise in pharmaceutical research, where machine learning algorithms expedite the identification of potential drug candidates, predict molecular interactions, and optimize clinical trials (Mak and Pichika, 2019). This accelerates the traditionally lengthy and costly drug development process. Thus, the potential benefits of AI adoption in healthcare are considerable, particularly for developing countries like Vietnam.

Besides those applications of AI in healthcare, one of the most prominent and impactful applications is AI-based medical decision support systems (AIMDSS), a system that assists users with timely, accurate, and relevant diagnostic suggestions, treatment recommendations, and risk predictions by processing complex clinical data of patients (Fan *et al.*, 2020; Yang, Ngai and Wang, 2024). AIMDSS can be considered a form of narrow AI, as they are designed to perform specific, well-defined clinical tasks. In healthcare, AIMDSS typically exist in an embedded form within medical devices or clinical information systems, where they analyze domain-specific data such as medical images, endoscopic videos, or patient records to support physicians in diagnosis and clinical decision-making under human supervision (Fan *et al.*, 2020; Li and Wang, 2024). These systems have shown measurable benefits in reducing diagnostic errors, improving clinical efficiency, and enabling evidence-based decision-making (Fan *et al.*, 2020; Li and Wang, 2024). The adoption of AIMDSS is considered as the solution to misdiagnosis and low efficiency in medical diagnosis, which are major issues in developing countries (i.e., China, Vietnam, etc) (Fan *et al.*, 2020; Tran *et al.*, 2021). AI in diagnostics has seen particular success in medical imaging and pathology. Deep learning models are now capable of detecting abnormalities in radiological scans (e.g., CT, MRI, and X-rays) with accuracy comparable to, and in some cases exceeding, that of human experts (Fan *et al.*, 2020). These tools are increasingly deployed in radiology, dermatology, and ophthalmology for tasks such as tumor detection, diabetic retinopathy

screening, and fracture identification¹. An example of an AIMDSS in Vietnam is the well known DrAid, developed by VinBrain, which was subsequently sold to tech giant NVIDIA in 2024 (VietNamNet, 2024). Given the increasing use and the availability of AIMDSS in Vietnam (Thu, Nguyen and Taylor-Robinson, 2023), this dissertation investigate the determinants of consumers' intention to adopt this specific AI in their healthcare services. In this dissertation, the author would use AIMDSS and medical AI interchangeably to refer to AI based systems that support clinical decision making.

Medical AI is transforming healthcare service delivery, yet facing consumers's resistance

Despite its advantages in providing efficient and timely services, the adoption of AI in healthcare settings faces a critical challenge, which is the adoption by healthcare professionals and consumers/patients. The transition from the traditional healthcare context, where services are primarily delivered by physicians with the support of health information technology (HIT), to the emerging model in which medical AI systems collaborate with physicians to provide care to patients, is illustrated in Figure 1.1. Health information technology (HIT) refers to integrated systems that collect, store, manage, and transmit information related to the health of individuals or activities of organizations, such as electronic health records (EHRs), hospital information systems, and telemedicine platforms (Bhattacharjee and Hikmet, 2007; Yang, Ngai and Wang, 2024). Compared with traditional health information technology (HIT), medical AI possesses three distinctive characteristics: (1) the ability to make autonomous decisions without human intervention, (2) the capacity for self-learning that improves through exposure to data and experience, and (3) an inherent opacity that makes its decision-making processes difficult for users to interpret (Berente *et al.*, 2021; Yang, Ngai and Wang, 2024). These unique characteristics raise various concerns for patients regarding privacy protection, the lack of transparency in AI-generated diagnoses, and unclear legal accountability. Such challenges highlight that adoption of medical AI is fundamentally different from that of traditional HIT, as AI systems do not merely process or transmit information but actively participate in clinical reasoning and decision-making.

In the emerging health service context, the medical service is delivered jointly by both physician and medical AI, and the former is the one who has the final decision on diagnosis and treatment of the patients. However, it would be a shortcoming to overlook consumers' intention to adopt medical AI in their healthcare services. In healthcare, autonomy is a fundamental ethical principle that affirms a patient's right to make

¹ Illustration of AIMDSS systems and its application is in the Appendix 3, in which author provided definition and example of the systems.

informed decisions about their own care (Pham, 2025). As healthcare delivery increasingly incorporates AI technologies, patients must therefore be informed about how these tools are used in diagnosis and treatment and the implication for their health outcomes, as illustrated in the emerging health service context shown in Figure 1.1. This requires transparent communication about the role of AI in clinical decision-making, its limitations and uncertainties, and the patient’s right to seek second opinions or choose alternative options (Pham, 2025). Accordingly, patients and healthcare consumers should possess full awareness and autonomy when deciding whether to accept or decline the use of medical AI within their care. As developing countries such as Vietnam move toward building regulatory frameworks for medical AI (Chanh *et al.*, 2023), consumers are expected to play a more active role in these decisions, replacing the current ambiguity surrounding AI use in healthcare.

Despite medical AI’s advancement, existing studies suggest that consumers resist to adopting this technology in their healthcare services (Khanijahani *et al.*, 2022; Li and Wang, 2024; Yang, Ngai and Wang, 2024). Evidence from more developed countries indicates that many patients express hesitation or resistance toward medical AI due to concerns related to safety, trust, uniqueness neglect, and ethical transparency (Jain, Wadhwani and Eastman, 2024; Yang, Ngai and Wang, 2024; Li and Wang, 2024; Longoni, Bonezzi and Morewedge, 2019). Thus, in order to support wider adoption and reduce disparities in healthcare quality across regions, gaining a deeper understanding of consumer acceptance of medical AI in Vietnam is both timely and essential. In particular, this dissertation would focus on examining factors determining consumers’ intention to adopt AIMDSS in Vietnam.

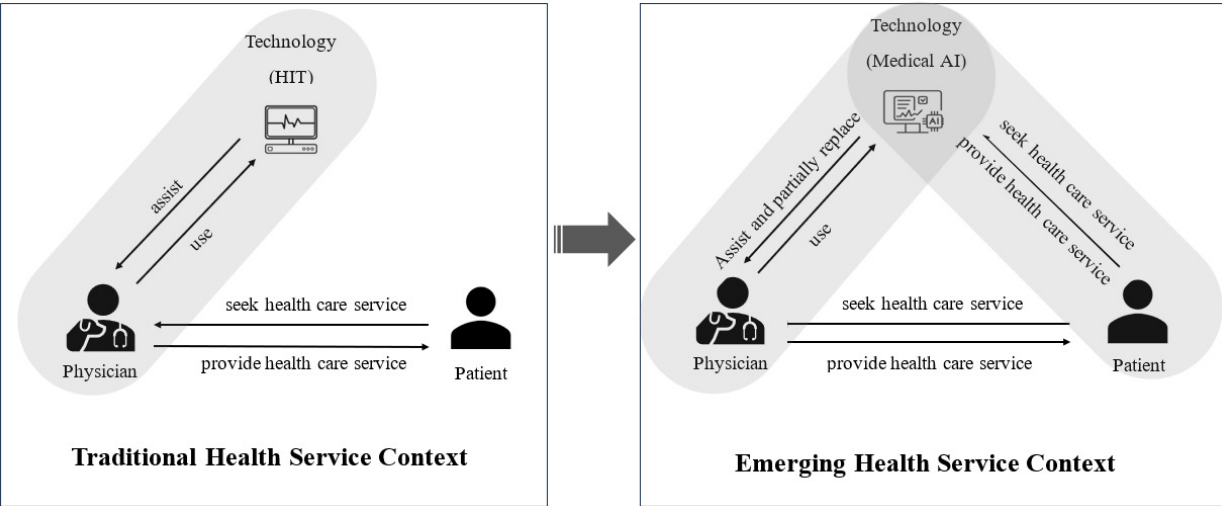


Figure 1.1. The relationship among technology, physician and patient

Source: Yang et al. (2024)

1.1.2. Consumers' adoption of AI in healthcare

1.1.2.1. Consumers' adoption of AI in healthcare: an emerging topic

Over the past two decades, the domain of consumer behavior has undergone a substantial transformation, largely driven by rapid advancements in artificial intelligence (AI). In today's volatile and fast-evolving marketplace, consumer needs, preferences, and behaviors continue to shift at an unprecedented pace. To remain competitive and responsive to these changes, organizations are increasingly integrating AI technologies across a range of business functions. AI enables firms to deliver highly personalized customer experiences, optimize market segmentation, improve targeting precision, and automate various marketing and operational tasks, resulting in enhanced efficiency, scalability, and accuracy. The expanding capabilities of AI have moved beyond routine automation to encompass complex cognitive functions, including those that require adaptive decision-making and contextual comprehension (Dwivedi *et al.*, 2021). Consequently, the deployment of AI now spans nearly all sectors, including highly sensitive and knowledge-intensive domains such as healthcare. In this context, AI has evolved from being a source of strategic differentiation to an essential infrastructure for organizational sustainability and growth.

In response to these shifts, Jain et al. (2024) conducted a comprehensive review and identified five prominent research themes that define the intersection of AI and consumer behavior. These themes include: (1) the impact of AI on consumer behavior; (2) consumer decision-making processes involving AI agents; (3) consumer adoption of AI technologies; (4) acceptance and trust in AI systems; and (5) consumer perceptions of and emotional responses to AI.

Among the five major research clusters on artificial intelligence (AI) and consumer behavior, clusters three (consumer adoption), four (trust and acceptance), and five (perception and response) are especially salient and closely interconnected. Indeed, these topics have received increasing attention in recent years. Given the increasing application of medical AI in healthcare services, understanding factors that shape consumers' attitude and intention to adopt medical AI is considered as a key stream of research in AI adoption studies in recent years (Khanijahani *et al.*, 2022; Yang, Ngai and Wang, 2024; Jain, Wadhwani and Eastman, 2024). A review by Yang et al. (2024) shows that the number of publications on medical AI adoption has surged notably since 2020, reflecting increasing attention to this topic. Studies also suggest that consumers's resistance toward medical AI is ongoing, despite AI's advancement

in the field of healthcare (Longoni, Bonezzi and Morewedge, 2019; Yang, Ngai and Wang, 2024). Moreover, Yang et al. (2024) noted that research in this domain remains in its infancy and that the existing body of knowledge is still fragmented. Thus, there is a strong need for further investigation into AI adoption intention and its driving factors for underexplored services in specific and impactful contexts such as healthcare (Jain, Wadhwani and Eastman, 2024, p. 16; Yang, Ngai and Wang, 2024).

1.1.2.2. Consumers' adoption of medical AI in studies

The need for new theoretical perspectives on AI Adoption in healthcare

Given the increasing attention to understanding determinants of AI adoption, numerous studies have investigated this issue through various theoretical lenses. This section reviews key theories that have been commonly employed to study AI adoption. In the field of consumer behavior, several theories have been applied to study AI adoption, including the Technology Acceptance Model, the Theory of Planned Behavior, the Unified Theory of Acceptance and Use of Technology, the Artificially Intelligent Device Use Acceptance model, the Value-Attitude-Behavior model and Uniqueness theory (Prakash and Das, 2021; Khanijahani *et al.*, 2022; Mariani, Perez-Vega and Wirtz, 2022; Jain, Wadhwani and Eastman, 2024).

In the healthcare domain, research often relies on established theories such as TAM, TPB, and UTAUT to study medical AI adoption (Prakash and Das, 2021; Mariani, Perez-Vega and Wirtz, 2022). For example, Ye et al. (2019) employed TPB in a cross-sectional study of healthcare professionals in China, found that attitude, subjective norm, and perceived behavioral control significantly predicted intention to adopt AI, with perceived risk and trust acting as important mediators. In healthcare contexts, Fan et al. (2020) applied UTAUT to medical professionals' adoption of AI-based diagnostic support systems, identifying performance expectancy, effort expectancy, and facilitating conditions as significant predictors of adoption intention. Similarly, Tran et al. (2021) found that among Vietnamese prospective physicians, behavioral intention to use AI-assisted diagnosis was strongly influenced by performance expectancy, professional demand, and perceived organizational support. However, past research has also suggested that TAM and UTAUT leave out social and cultural factors in explaining technology adoption behavior (Bagozzi, 2007; Ho *et al.*, 2022). In addition, some limitations associated with TAM in studying healthcare have been noted (Holden and Karsh, 2010). Holden and Karsh (2010) suggested that while TAM can predict a

substantial portion of health-IT acceptance, the theory have not accounted sufficiently for the complex contextual factors and the salient beliefs that influence technology use in healthcare settings. Furthermore, there is a call for examining the determinants of medical AI adoption from another theoretical perspective (Jain, Wadhvani and Eastman, 2024).

Some other emerging theoretical approach is uniqueness theory, proposed by Snyder and Fromkin (1980), posits that individuals have a fundamental motivation to perceive themselves as distinct from others, and this need for uniqueness influences their attitudes, preferences, and behaviors. The theory suggests that people strive to maintain an optimal level of distinctiveness, avoiding excessive similarity with others while also steering clear of extreme deviation that may result in social isolation or rejection. In consumer behavior research, the need for uniqueness has been linked to the adoption of innovative products, non-conformist brand preferences, and early adoption of emerging technologies (Tian, Bearden and Hunter, 2001). Longoni et al. (2019) conducted a series of experiments to investigate consumer resistance to medical artificial intelligence, demonstrating that people often prefer human physicians over equally or more accurate AI systems. Drawing on uniqueness theory, they found that this resistance was partly driven by the perception that AI-provided care lacks personalization and fails to acknowledge patients' individual characteristics. Their findings suggest that when individuals perceive themselves as unique, they are more likely to distrust algorithmic recommendations and favor human judgment, even at the expense of accuracy. This highlights the relevance of uniqueness needs in shaping attitudes toward AI in healthcare. Furthermore, it reflects a human-centered belief that people are inherently more capable than machines in performing judgment-intensive tasks, aligning with the core tenets of anthropocentrism.

To address limited attention to contextual and motivational factors of previous theories, Westaby (2005) introduced Behavioral Reasoning Theory (BRT), building on the Theory of Planned Behavior to explain the role of behavioral rationality in individual decision-making. Behavioral rationality refers to the reasons that motivate individuals to support or oppose specific behaviors (Westaby, 2005). As outlined by Westaby (2005), human beliefs or values shape these reasons, which in turn function as proximal determinants of attitudes and intentions. By emphasizing the central role of human reasoning in linking beliefs, motives, and behavioral intentions, BRT provides a comprehensive framework for understanding consumer decision-making in complex technological contexts. In healthcare domain, Li and Wang (2024) found that

Chinese consumers' value of "openness to change" significantly influenced their reasons for and against adopting AI-assisted diagnostic systems (AIMDSS), and those context-specific reasons played a central mediating role in shaping both attitudes toward and intention to adopt AIMDSS. Despite the growing use of BRT in consumer behavior research, including studies on AI adoption, its applications have predominantly focused on values, leaving the influence of human beliefs on consumers' intentions to adopt products or services relatively understudied (Sahu, Padhy and Dhir, 2020; Jain, Wadhwani and Eastman, 2024; Westaby, Rosemarino and Elliot, 2025). Additionally, Mariani et al. (2022) suggest that the reasons supporting or opposing AI adoption differ markedly between healthcare and consumer-goods contexts. Thus, employing BRT would offer deeper insights into the factors that facilitate or hinder AI adoption across these distinct settings, such as human beliefs and context-specific reasons.

The predominance of quantitative methods and the call for new insights

Regarding research methodology, as illustrated in Figure 1.2, Jain et al. (2024) reveals a clear methodological inclination toward experimental research designs, which constitute 67 out of 107 studies, making it the most dominant approach. This indicates a strong preference in the field for controlled testing of causal hypotheses, particularly in consumer behavior contexts where experimental realism and internal validity are prioritized. In contrast, traditional quantitative (11 studies), qualitative (5), mixed-method (6), and computational research (5) remain relatively underrepresented, highlighting an opportunity for methodological diversification in future research. The low count of qualitative and mixed methods is particularly notable given the increasing recognition of the need to explore contextual and subjective experiences in AI adoption. Conversely, in healthcare settings, experimental methods are rare. Both Khanijahani et al. (2022) and Roppelt et al. (2024) found that most healthcare AI studies are cross sectional surveys, and only 3 studies used experimental methods among the 130 reviewed by Roppelt et al. (2024). Furthermore, SEM remains a prevalent technique, especially in healthcare (e.g., 11 out of 27 in Khanijahani et al. (2022); 15 out of 130 in Roppelt et al. (2024)), though it is used more extensively in consumer-focused research. Therefore, this reflects a substantial methodological gap. Jain et al. (2024) suggest that there is a dearth of studies using qualitative, and mixed method approaches. Moreover, Jain et al. (2024) suggests the employment of these methods are necessary to ideate new concepts and linkages, and promote better understanding of consumers' adoption of AI.

This need is particularly salient in complex contexts such as healthcare, where adoption decisions are shaped by multifaceted cognitive and contextual factors.

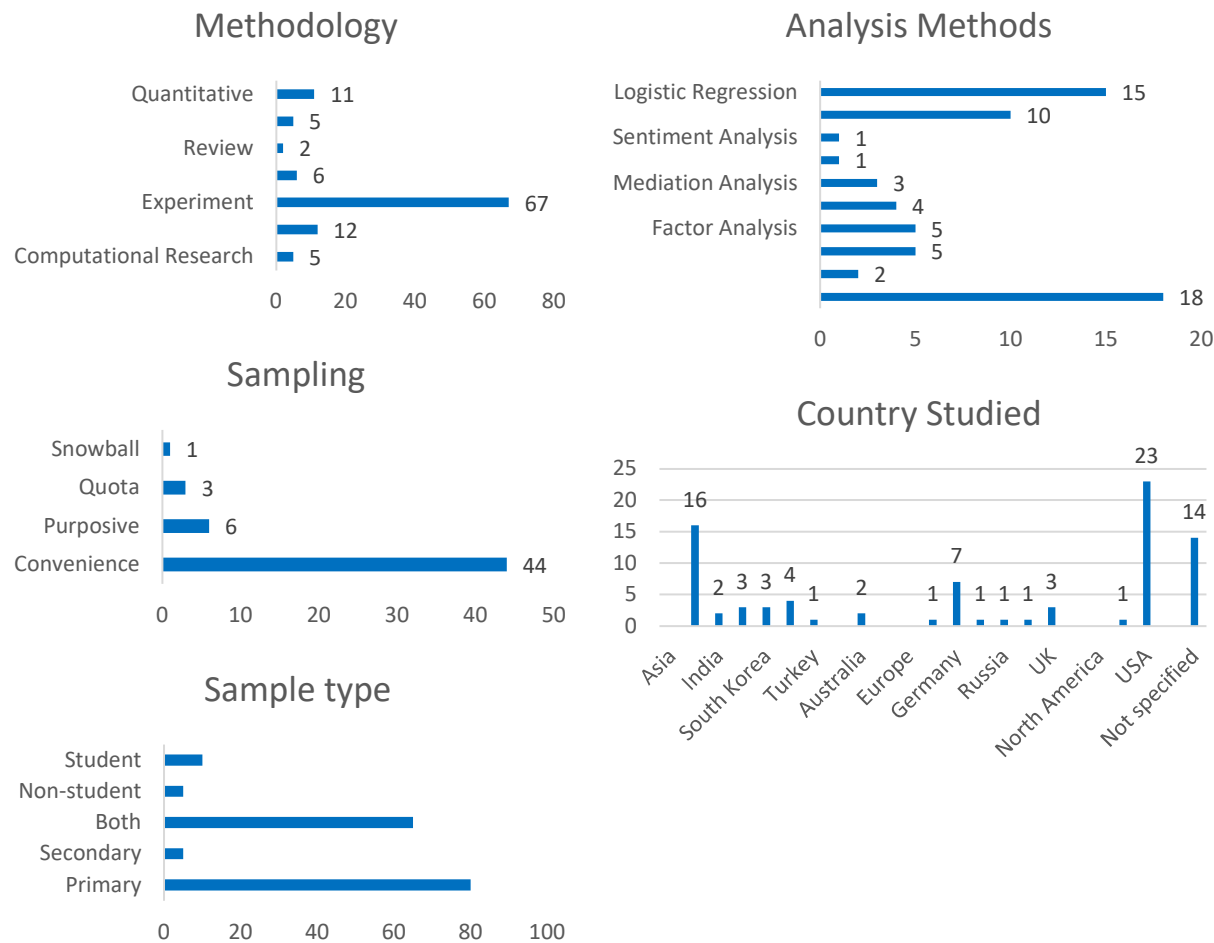


Figure 1.2. Research design characteristics in literature

Source: Jain et al. (2024)

Limited evidence from developing countries beyond China

As Jain et al. (2024) argue, there is a growing need to incorporate cultural and societal considerations into AI consumer behavior research, particularly in non-Western and under-researched contexts. Most existing studies are situated in technologically advanced or Western countries, leaving a gap in the understanding of how consumers in emerging markets perceive and adopt AI. In this context, a developing country (e.g. Vietnam) represents a timely and relevant case, where medical AI is still novel yet increasingly visible. Despite growing consumer familiarity with AI through tools like ChatGPT, the willingness to adopt AI in

sensitive domains such as healthcare, and the reasons underlying such decisions in developing countries remain underexplored. Consequently, this area remains a promising avenue for future research. Geographically, the USA (23) and Asia (16) dominate the research landscape, with China (6) and South Korea (4) as major contributors in Asia. A concerning gap remains in representation from many other global regions, particularly low- and middle-income countries, where contextual differences in infrastructure, digital literacy, and cultural values could significantly alter AI adoption outcomes. Additionally, 14 studies did not specify the country studied, limiting the transparency and comparability of results across contexts. To promote fair and inclusive application of medical AI in developing countries, equitable research attention to developing countries beyond China is needed. That also help medical AI companies to design products that better meet the needs, concerns, and expectations of diverse consumer populations. Therefore, expanding research into underrepresented regions and employing mixed-method designs can yield context-specific insights that enhance both theoretical development and practical applications.

1.1.3. Determinants of behavioral intention to adopt medical AI in healthcare

Given the increasing integration of artificial intelligence (AI) across various domains, a growing body of research has sought to assess its potential benefits and risks, and explore the complex dilemmas arising from heightened human–AI interaction (Kelly, Kaye and Oviedo-Trespalacios, 2023). While there is a broad consensus on AI’s expanding role and capabilities, public responses have been mixed. On one hand, AI is viewed as a supportive tool that can alleviate human workload, enhance efficiency, and improve decision-making (Davenport and Kalakota, 2019; Shamszare and Choudhury, 2023; Cordina *et al.*, 2024). On the other hand, concerns have emerged about AI’s potential to blur the boundaries of human identity, autonomy, and safety, particularly in sensitive or high-stakes domains (Złotowski, Yogeewaran and Bartneck, 2017; Mirbabaie *et al.*, 2022; Federspiel *et al.*, 2023). In healthcare, these tensions are especially salient, as AI’s role in diagnosis and treatment raises questions about its reliability and the preservation of empathetic human care.

Consumer adoption of AI in healthcare is shaped by a multifaceted array of individual and psychosocial determinants. Among these, psychosocial factors have emerged as particularly influential, encompassing both cognitive and emotional evaluations of the technology (Khanijahani *et al.*, 2022). Core drivers include perceived usefulness and performance expectancy, reflecting individuals’ belief in AI’s ability to enhance diagnostic or treatment outcomes, alongside effort expectancy or the perceived

ease of using such systems (Khanijahani *et al.*, 2022; Roppelt, Kanbach and Kraus, 2024). Trust plays a central role in adoption decisions, as consumers often weigh potential benefits against perceived risks, such as data privacy concerns or fears of clinical harm (Khanijahani *et al.*, 2022; Jain, Wadhvani and Eastman, 2024). Social factors also exert considerable influence, as subjective norms and perceived social pressure have been shown to shape willingness to adopt medical AI, particularly in collectivist cultural contexts (Roppelt, Kanbach and Kraus, 2024). Beyond these general predictors, individual characteristics further differentiate adoption behavior. Variables such as age, gender, education, and race may moderate perceptions of AI and its appropriateness in healthcare contexts (Khanijahani *et al.*, 2022). Also, personal innovativeness and prior exposure to AI applications contribute to greater openness, while situational factors, such as illness severity or prior experiences with misdiagnosis, may intensify the motivation to consider AI-based interventions (Khanijahani *et al.*, 2022; Roppelt, Kanbach and Kraus, 2024). Importantly, recent studies highlight a distinct psychological barrier, consumers' "sense of uniqueness", which reflects concern that AI might overlook the individualized nature of human care, leading to resistance even in the presence of demonstrable performance benefits (Longoni, Bonezzi and Morewedge, 2019; Jain, Wadhvani and Eastman, 2024). Despite a number of studies on AI adoption in healthcare, consumers' receptivity toward medical AI remains insufficiently understood (Khanijahani *et al.*, 2022). Table 1.2 summarizes findings from key studies on factors affecting consumers' adoption of medical AI. Taken together, these studies reveal that reactions to medical AI often hinge on deeper assumptions about the appropriate role of humans in healthcare and the anticipated benefits of technological advancement. Thus, in an era where novel technologies can simultaneously empower and threaten humans' sense of centrality, safety, and uniqueness, belief systems such as anthropocentrism and techno-optimism likely shape how consumers interpret reasons for and against using medical AI and therefore deserve further examination. Despite that, there is limited attention given to such underlying belief systems that shape consumers' psychological reasoning about AI technologies. To better understand the impact of belief on adoption behavior, BRT emerges as an appropriate theoretical lens to study how beliefs influence attitude and intention to adopt AIMDSS, via the reasoning process (Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025).

Table 1.2. Summary of key papers on consumers' adoption of medical AI

Author	Manuscript title Publication journal	Methodology	Key Findings
Longoni et al. (2019)	Resistance to Medical Artificial Intelligence <i>Journal of Consumer Research</i>	Utilized a series of 11 studies with U.S. adults, using real-world choices, choice-based conjoint exercises, and scenario-based experiments. Compared consumer preferences for AI vs. human providers in medical contexts (e.g., stress diagnosis, skin cancer screening, surgery)	Consumers resistance to medical AI in both real and hypothetical choices. Consumers tend to engage less with healthcare services, assign lower willingness to pay for such services, show reduced sensitivity to variations in provider performance and experience decreased satisfaction or utility when the provider is automated rather than human. Further, people resist AI medical decisions because they believe AI cannot consider their unique personal characteristics. Resistance is reduced when the AI is framed as "personalized" or when the AI only supports (rather than replaces) a human doctor.
Esmailzadeh (2020)	Use of AI-based tools for healthcare purposes: a survey study from consumers' perspectives <i>BMC Medical Informatics and Decision Making</i>	Cross-sectional online survey of 307 U.S. consumers using a value-based adoption model. Structural equation modeling tested relationships between perceived benefits, risks, and intention to use AI-based clinical decision support tools.	Perceived risk and perceived benefits are key predictors of intention to adopt AI-based tool in healthcare by consumers. Perceived risks were shaped by three factors: technological (e.g., performance anxiety), ethical (trust, privacy, bias), and regulatory concerns (liability, lack of standards). Technological concerns were most influential factors of perceived risk.

Author	Manuscript title Publication journal	Methodology	Key Findings
Frank et al. (2021)	Drivers and social implications of Artificial Intelligence adoption in healthcare during the COVID-19 pandemic <i>PLOS ONE</i>	Representative cross-sectional survey (N=1068) conducted in Denmark (n=566) and France (n=602) Data collected during the first wave of the COVID-19 pandemic (April-May 2020). Used a hypothetical scenario for COVID-19 triage, asking participants to choose between a human physician or a medical AI. Analyzed using generalized linear regressions.	Found strong AI aversion: only about 1 in 10 individuals (less than 10%) chose medical AI over a human physician. Key predictors for AI adoption were trust in medical AI (the strongest factor) and the trait of open-mindedness. AI adoption also significantly increased due to mistrust in human physicians, perceived uniqueness neglect from human physicians, and a lack of social belonging.
Gaczek et al. (2023)	Overcoming Consumer Resistance to AI in General Health Care <i>Journal of Interactive Marketing</i>	Five experimental studies using vignettes (scenarios) about a medical app Employed 2x2 experimental designs (Provider: AI vs. Human; Diagnosis: Good vs. Bad) Analyzed moderation (e.g.,	Identified a “good news/bad news effect”: consumers are less likely to trust and follow AI recommendations when the diagnosis shows good health. However, when the diagnosis was bad news (worrisome symptoms, requiring emergency care), consumers showed no difference in willingness to follow AI vs. human advice. This effect was mediated by diagnosis trustworthiness and amplified in

Author	Manuscript title Publication journal	Methodology	Key Findings
		health anxiety) and mediation (e.g., trustworthiness) using the PROCESS macro	people with high health anxiety. Also, social proof (peer endorsement) reduces resistance and increases compliance.
Ho et al. (2023)	Understanding the acceptance of emotional artificial intelligence in the Japanese healthcare system: A cross-sectional survey of clinic visitors' attitudes <i>Technology in Society</i>	Cross-sectional municipal survey of 245 clinic visitors in suburban Japan; multiple regression analyses examined socio-demographic and attitudinal correlates.	Older and male patients generally perceived EAI more negatively. Familiarity with AI had a strong positive correlation with attitudes toward EAI. Concern over losing control to AI had a significant negative correlation with attitudes. In contrast to other literature, concerns over privacy and discrimination were <i>non-significant correlates</i> .
Huo et al. (2024)	Speciesism and Preference of Human–Artificial Intelligence Interaction: A Study on Medical Artificial Intelligence <i>International Journal of Human–Computer Interaction</i>	Two-wave survey of 249 patients in China during COVID-19; structural modeling tested effects of speciesism, trust, and human uniqueness perception.	Introduced speciesism as a novel cognitive barrier to AI in healthcare. Found that high speciesism lowered acceptance of AI in independent roles but raised acceptance when AI assists doctors. Human–computer trust mediated these effects; perception of human uniqueness strengthened the negative impact of specism on trust.

Author	Manuscript title Publication journal	Methodology	Key Findings
Li and Wang (2024)	Determinants of artificial intelligence-assisted diagnostic system adoption intention: A behavioral reasoning theory perspective <i>Technology in Society</i>	Cross-sectional survey applying BRT tested reasons for and against adoption among 415 healthcare consumers in China.	The personal value of "openness to change" significantly impacts attitudes and reasons (for/against). <i>Reasons for</i> (e.g., initial trust, professional level) positively predict attitude and intention. <i>Reasons against</i> (including uniqueness neglect and privacy concerns) negatively predict attitude and intention. Attitude fully mediated the effect of reasons on intention.
Kumar et al. (2025)	Customer adoption of artificial intelligence in healthcare: An empirical investigation based on multiple samples <i>Health Marketing Quarterly</i>	Multi-sample survey across three AI role scenarios (supporting, augmenting, performing) in India; N≈1,500 analyzed with PLS-SEM and Multi-Group Analysis.	Employed Theoretical Framework: Extended UTAUT (Unified Theory of Acceptance and Use of Technology), adding "creepiness," privacy concerns, and trust. Key factors affecting adoption are: Performance expectancy, privacy concerns, trust, and social influence. Privacy concerns and the need for human interaction predict "creepiness". "Creepiness" negatively affects trust. Trust positively predicts behavioral intention. MGA shows the strength of these relationships varies by AI role (e.g., Effort expectancy was non-significant in the AIA role but significant in AIS and AIP roles)

1.1.3.1. Reasons for adopting AIMDSS of consumers

From BRT perspective, individuals' intentions to engage in a particular behavior are contingent on the reasons they construct to justify that behavior (Westaby, 2005). Specifically, Westaby (2005) conceptualizes reasons as "specific subjective factors people use to explain their anticipated behavior," which serve as the immediate cognitive link between deeper beliefs and behavioral intentions. Accordingly, consumers may hold different reasons for and against adopting medical AI. Following Westaby (2005), *reasons for* and *reasons against* are conceptualized as multidimensional constructs, each constituted by multiple context-specific variables that collectively capture individuals' justifications for supporting or opposing a given behavior. The details of these constructs are discussed further in the section 1.2.1.

As BRT posits that reasons are inherently context specific (Westaby, 2005), the nature of consumers' justifications for adopting medical AI is likely to depend strongly on the stage of technological diffusion and local conditions. In developing countries such as Vietnam, where medical AI adoption remains at a nascent stage, consumers may have limited exposure to and understanding of this technology. Prior research consistently highlights the pivotal role of trust in shaping consumer behavior, particularly in the adoption of novel technologies (Jarvenpaa, Tractinsky and Vitale, 2000; Li, Hess and Valacich, 2008). Trust in AI is especially critical, as it functions as a prerequisite for individuals' willingness to accept and rely on AI systems (Nguyen and Vu, 2023), and has been identified as a key antecedent of AI adoption across multiple domains (Park, Tung and Lee, 2021), including healthcare settings (Wei *et al.*, 2024). By reducing perceived complexity and uncertainty, trust facilitates consumers' readiness to engage with unfamiliar technologies (Tao *et al.*, 2020). In the absence of prior direct experience, consumers tend to rely on institutional cues to infer the expected benefits of a technology (McKnight *et al.*, 2011) and to form initial trust judgments (McKnight, Cummings and Chervany, 1998). Accordingly, initial trust is likely to emerge as an important context-specific reason for supporting the adoption of AIMDSS in the Vietnamese healthcare context.

Initial trust

Initial trust refers to the willingness to rely on a product, service, or system in the absence of prior experience or interaction, often formed on the basis of limited cues such as reputation, structural assurances, or third-party endorsements (McKnight, Cummings and Chervany, 1998). Trust, more broadly, encompasses a user's readiness to depend on another entity and typically progresses through three stages: initial trust formation, trust

development, and potential trust deterioration (Davis, Bagozzi and Warshaw, 1989). In the context of technology adoption, initial trust plays a pivotal role in shaping early user attitudes and intentions, particularly when individuals are unfamiliar with the system's performance or outcomes. This is especially relevant for emerging health technologies such as Artificial Intelligence-powered Medical Decision Support Systems (AIMDSS), where users must often make judgments under uncertainty and with limited hands-on experience. Trust in the system's reliability, accuracy, and alignment with ethical medical standards becomes a critical cognitive anchor in the decision-making process. When users initially trust the system, they are more likely to form favorable evaluations of it and perceive it as reliable, secure, and aligned with legal and ethical standards. This perception may reduce their anticipation of negative outcomes, such as diagnostic errors, thereby increasing their likelihood of engaging with and adopting the system. Empirical research supports the role of initial trust in influencing adoption behavior; for example, Lee and See (2004) and Zhang et al. (2019) found that higher levels of initial trust in AI systems significantly increased users' acceptance in safety-critical domains, including healthcare. Thus, within the framework of BRT, initial trust serves as a salient "reason for" adoption, providing users with a defensible rationale for engaging with AIMDSS despite its novelty and perceived risks.

Modern self

To study medical AI adoption in a developing country such as Vietnam, it would be a significant shortcoming to overlook psychocultural factors that shape how consumers perceive and evaluate new technologies (Khanijahani *et al.*, 2022; Jain, Wadhwani and Eastman, 2024). Vietnam is a transitional economy in which rapid modernization and exposure to global influences coexist with deeply rooted traditional values, leading individuals to hold multiple, and sometimes conflicting self-concepts (Nguyen, Smith and Cao, 2009). In such context, self-concept becomes a critical lens through which consumers interpret whether medical AI aligns with or threatens their identity, social norms, and expectations of care. These identity-based evaluations are likely to emerge as context-specific reasons for or against adoption, beyond purely functional or technological considerations. Therefore, incorporating self-concept into the analysis enables a more nuanced understanding of medical AI adoption by capturing the underlying cultural and identity-driven motivations that are particularly salient in transitional healthcare settings.

Self-concepts have been recognized as influential determinants of consumer attitudes and, consequently, behavioral intentions toward adopting new products and

services (Jamal, 2004; Wu and Chan, 2011). Prior research indicates that self-concept is not static but evolves in response to socioeconomic transformations (Markus and Wurf, 1987). In transitional economies such as Vietnam and China, multiple self-concepts can coexist within an individual as a result of the influx of foreign cultural values (Zhang and Shavitt, 2003; Nguyen, Smith and Cao, 2009). Consumers utilize a dual-self dynamic as a coping strategy to resolve between traditional and modern cultural systems (Lu and Yang, 2006; Zhao *et al.*, 2019). In the context of Asian transitional markets, Nguyen et al. (2009) conceptualize consumer self-concept as comprising two distinct but coexisting dimensions: the traditional self (TS) and the modern self (MS). The modern self reflects individualistic and progressive consumer values, characterized by openness to innovation, preference for new experiences, and a desire for autonomy and flexibility in consumption choices. Thus, in the domain of technology adoption, the modern self may influence individuals' willingness to engage with advanced technologies that symbolize modernity, efficiency, and forward-thinking values. This is particularly relevant in healthcare, where emerging technologies such as Artificial Intelligence-powered Medical Decision Support Systems (AIMDSS) are perceived not only as functional tools but also as markers of medical modernization. Individuals who identify with a modern self are more likely to adopt AIMDSS, as doing so reinforces their self-image as technologically progressive and responsive to cutting-edge solutions. In the technology-related consumption domain, past research indicates that self-concept plays a pivotal role. Consumers evaluate offerings more favorably when a brand's identity matches how they see themselves, as shown by positive reactions to robotic coffee shops and by preferences for online banking brands that mirror one's self-view (Jamal, 2004; Kim and Ryu, 2021). Likewise, individuals who consider themselves tech-savvy tend to hold more positive attitudes toward high-tech products and services, thereby reinforcing that identity (Sirgy, 1985). Within the BRT, the modern self serves as a salient "reason for" adoption, offering users an identity-based rationale for engaging with AIMDSS as a reflection of their modern orientation.

Personal innovativeness in the domain of health technology

Personal innovativeness in the domain of health technology (PIHT) refers to an individual's willingness and tendency to try out novel health-related technologies, particularly in the early stages of their diffusion. This construct is adapted from Agarwal and Prasad's (1998) definition of personal innovativeness in the domain of information technology (PIIT), which captures the degree to which an individual is predisposed to adopt new information technologies independently and ahead of others. In the context

of technology adoption, PIIT has been consistently associated with greater acceptance and usage of emerging digital tools, especially when uncertainty or complexity is high (Yi, Fiedler and Park, 2006). For example, Agarwal and Karahanna (2000) showed that highly innovative individuals experience stronger cognitive absorption when interacting with new technologies, which in turn enhances perceived usefulness and behavioral intention to adopt new technology. In a mobile technology context, PIIT was found to positively affect perceived usefulness, perceived ease of use, and adoption intention, indicating that innovative individuals are more receptive to emerging IT services (Lu, Yao and Yu, 2005). In the healthcare domain, empirical evidence suggests that physicians with higher PIIT perceive AIMDSS as less complex and easier to use, which in turn fosters greater confidence and trust in the technology and increases their willingness to adopt it (Fan *et al.*, 2020). Despite that, this construct may not fully translate to healthcare contexts, where decisions involve substantially higher risk and personal consequences. For example, an individual who is highly innovative and willing to experiment with technologies such as generative AI (e.g., ChatGPT, Copilot) in daily life may nonetheless remain hesitant to rely on medical AI systems like AIMDSS when their own health and safety are at stake. Thus, an adaptation following the suggestion of Agarwal and Prasad's (1998) is needed to capture the complexity of medical AI adoption. Following relevant empirical evidence on PITT, personal innovativeness in the domain of health technology (PIHT) is likely to be key *reason for* adoption.

1.1.3.2. Reasons against adopting AIMDSS of consumers

Similar to reasons for, reasons against adoption are also inherently context specific. While a modern self is likely to function as a rationale supporting medical AI adoption, consumers who identify more strongly with a traditional self may resist this technology, as they tend to prefer conventional healthcare services that emphasize human interaction, empathy, and relational care. In addition, perceived threat represents another salient inhibiting factor in the adoption of medical AI, as AI systems are increasingly capable of performing complex tasks that were traditionally reserved for human professionals. Greater integration of medical AI may therefore heighten consumers' perceptions of identity threat, stemming from concerns about the erosion of human expertise and the doctor–patient relationship, as well as realistic threat related to diagnostic errors, safety risks, and accountability. Together, these concerns can activate strong reasons against adoption, tempering consumers' willingness to embrace medical AI even when it is positioned as an assistive rather than autonomous technology.

Traditional self

In contrast to MS, the traditional self (TS) reflects continuity with long-standing cultural norms and social expectations. Nguyen et al. (2009) associate the traditional self with values rooted in respect for the past, adherence to social conventions, and caution toward new products or services. In the context of technology adoption, particularly in culturally embedded, high-stakes domains such as healthcare, this dissertation posits that the traditional self is associated with a conservative stance toward innovation. Consumers with a strong traditional self are more inclined to favor familiar, human-centered systems over algorithmic or automated alternatives. When applied to medical AI technologies like AIMDSS, the traditional self may generate skepticism toward automated decision-making, perceiving it as inconsistent with established doctor-patient dynamics and cultural expectations of care. This resistance stems from concerns over losing human oversight, relational trust, and moral accountability in healthcare delivery. Empirical research supports this notion, showing that individuals with stronger traditional orientations tend to exhibit weaker preferences for new products (Javalgi *et al.*, 2013). Following BRT, the traditional self may serve as a meaningful justification for consumers' hesitation to adopt medical AI.

Perceived threat

According to Witte (1992), a threat is defined as an external stimulus with the potential to cause harm, regardless of whether individuals are consciously aware of it. Perceived threat, therefore, refers to an individual's cognitive acknowledgment or belief that such a threat is present and personally relevant. In the context of medical artificial intelligence, particularly Artificial Intelligence-powered Medical Decision Support Systems (AIMDSS), patients may worry that the technology may adversely affect their health outcomes, autonomy, or the human elements of care (Akingbola *et al.*, 2024; Perrone, 2025). These concerns may not be based solely on technical knowledge but also on psychological, social, and cultural factors. This is especially relevant when patients (i.e., humans) consider their doctors as in-groups, while viewing medical AI (i.e., a non-human entity) as out-groups. Research on the psychology of intergroup relations has demonstrated that individuals tend to differentiate between ingroups and outgroups (Hewstone et al., 2002; Tajfel, 1974), often perceiving outgroups as threats (Alexander, 1974). Within this body of literature, scholars have identified two primary forms of threat posed by outgroups: realistic threats and identity threats (Stephan, Ybarra and Bachman, 1999; Riek, Mania and Gaertner, 2006). Realistic threats refer to perceived dangers to an ingroup's physical safety, material resources, or overall well-

being, while identity threats involve perceived challenges to the ingroup's distinctiveness, values, and cultural uniqueness (Stephan, Ybarra and Bachman, 1999; Riek, Mania and Gaertner, 2006; Huang *et al.*, 2021)

Regarding identity threat, when a group's uniqueness, particularity, or identity is threatened, it can also lead to prejudice, discrimination, and intergroup conflicts (Jetten, Spears and Manstead, 1996; Złotowski, Yogeeswaran and Bartneck, 2017). In that sense, consumers may perceive AI as posing an identity threat by blurring the boundary between what they consider distinctly human and what is performed by machines. People are concerned about the human-identity effect of AI, particularly when it can perform tasks traditionally performed by humans. Further, consumers would perceive their growingly faded uniqueness as they consider that AI would neglect their distinct identities (Longoni, Bonezzi and Morewedge, 2019). Research has shown that transformative technology (i.e., AI or AI anthropomorphic robots) can be seen as a threat to human identity and uniqueness and thus induce a negative attitude toward consumers (Longoni, Bonezzi and Morewedge, 2019). In the context of AIMDSS, patients may experience identity threat when they perceive that AI technologies diminish the relational and human-centered aspects of care that define their expectations of the healthcare system. For example, the reduced role of physicians in direct communication or decision-making may be interpreted as a threat to the distinctiveness of human caregiving. Patients who hold anthropocentric values, believing in the primacy of human roles in social and moral systems, may be particularly sensitive to identity threat. Thus, they would perceive AI as an inappropriate substitute for human expertise and empathy. As shown by Huang *et al.* (2021), identity threat significantly contributes to resistance toward AI technologies by challenging deeply held group norms and value structures.

As for realistic threat, it is increasingly prominent in recent years as scholars have argued that modern technology (i.e., AI and autonomous robots) is taking away power and control from humans (Złotowski, Yogeeswaran and Bartneck, 2017). According to Haggadone *et al.* (2021), the negative biases typically associated with human intergroup interactions are extended to human-robot interactions, as individuals tend to respond to robots in ways similar to how they react to human outgroup members. Therefore, humans may perceive AI (i.e., non-human) as threatening due to this intergroup bias. Studies have identified realistic threats as a barrier in consumers' adoption of non-human agents, such as AI and robots (Huang *et al.*, 2021; Liao *et al.*, 2024; Fiestas Lopez Guido *et al.*, 2025). In the medical context, patients may perceive realistic threats if they believe

AIMDSS could lead to misdiagnoses, compromised care quality, or reduced attention from human physicians, thus threatening their safety, physical, and mental well-being. Such concerns are heightened when patients lack control or understanding of how AI decisions are made, as research shows that interactions between intergroup agents are often perceived as threatening and unbeneficial due to mutual distrust stemming from a lack of shared characteristics or goals (Kappmeier, Guenoun and Fahey, 2021; Çakal *et al.*, 2021). Furthermore, patients who intrinsically believe that AI could generally take up their resources (jobs, income, opportunities) would perceive it as threatening and may maintain that stance in the healthcare context. Additionally, patients who emphasize anthropocentric worldviews may interpret AIMDSS as a system that devalues human judgment and introduces impersonal, mechanistic processes into healthcare. Given that consumers are likely to resist AI when they perceive it as posing identity and realistic threats (Mou, Gong and Ding, 2024), these factor may serve as a context-specific reason for consumers' hesitation to adopt medical AI.

Because reasons in BRT are inherently context-specific and medical AI adoption involves complex consumers' considerations, prior literature provides only a partial basis for identifying relevant reasons. Following established BRT research practices (Westaby, 2005; Claudy, Garcia and O'Driscoll, 2015), a qualitative phase was therefore conducted to elicit context-specific reasons for and against adopting medical AI.

1.1.3.3. Beliefs

Studying beliefs is essential because they constitute a fundamental component of human cognition, identity, and behavior, shaping decisions at both the individual and collective level, including the adoption of new technologies (Fishbein and Ajzen, 1975). Beliefs represent individuals' subjective probability judgments about specific aspects of the world, shaping how they interpret, evaluate, and respond to events or choices (Fishbein and Ajzen, 1975). Beliefs are core to the self, contributing to personality, uniqueness, and identity formation (Markus and Kitayama, 1998; Oyserman, Smith and Elmore, 2014). Moreover, beliefs exert transformative power over cognition, competencies, and attitudes (Bandura, 1989; Ajzen, 1991; Albarracín and Shavitt, 2018). A central tenet of psychological science is that holding a belief entails a perception of truth, which guides subsequent judgments and behaviors in either beneficial or detrimental ways (Albarracín *et al.*, 2005; Fishbein and Ajzen, 2010). In the attitudes–intention tradition, beliefs are the informational base from which attitudes, norms, and control perceptions are formed and updated (Fishbein and Ajzen, 1975, 2005). According to Rogers (2003), preadoption beliefs about an innovation serve as the

primary determinant of its eventual market acceptance or rejection. Indeed, technology adoption models, such as TAM, UTAUT (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003; Venkatesh and Bala, 2008; Venkatesh, Thong and Xu, 2012), are explicitly belief-based. Reviews and meta-analyses consistently show that these belief variables are strong predictors of adoption intention and use across settings, channels, and populations (Lee, Kozar and Larsen, 2003; King and He, 2006; Schepers and Wetzels, 2007; Khechine, Lakhal and Ndjambou, 2016).

In the domain of AI, research on the consumer adoption of this technology reveals a landscape of conflicting findings, indicating both significant receptiveness and notable resistance. A substantial body of work suggests that positive consumer sentiment is contingent upon several factors. Key among these are trust, perceived performance, perceived usefulness, and emotional engagement, which have been shown to foster an intention to adopt AI technologies (Ye *et al.*, 2019; Chatterjee *et al.*, 2021; Ma and Huo, 2023). Furthermore, the design of the user interface is critical, as human-like conversational interactions can increase user acceptance of AI advisors (Hildebrand and Bergner, 2021). In certain contexts, such as forecasting and personal decision-making, consumers have been found to prefer AI systems to human input (Logg, Minson and Moore, 2019). Conversely, considerable research also highlights significant barriers to AI adoption. This resistance is often attributed to algorithmic aversion, a bias against algorithm-based decision-making (Dietvorst, Simmons and Massey, 2015), and concerns that AI fails to account for individual uniqueness and context (Castelo, Bos and Lehmann, 2019; Longoni, Bonezzi and Morewedge, 2019). The contradictory results surrounding the adoption of AI point to a need to explore deeper psychological factors (von Walter, Kremmel and Jäger, 2022). Von Walter *et al.* (2022) further argued that consumers' beliefs about AI represent one of the most significant yet under-researched factors. Despite the growing prevalence of AI-enabled services in the marketplace, which makes beliefs highly influential, investigation into their nature and impact remains scarce (Huang and Rust, 2018). Therefore, a focused research effort on beliefs is not merely an incremental step but a necessary one to reconcile existing inconsistencies and build a more robust theory of AI adoption.

In the domain of consumer technology adoption, individuals may hold numerous beliefs about novel technologies. Consequently, identifying which beliefs become consequential for action is critical for understanding consumer acceptance of disruptive innovations such as medical AI. In this context, examining relevant belief structures, such as anthropocentrism and techno-optimism, becomes essential. These belief systems

may not only shape how consumers reason about the role of AI in healthcare but also provide insight into the cognitive processes that bridge beliefs and adoption intention. In this dissertation, the author adopts the belief categorization of Samayoa and Albarracín (2025) for conceptualisation of anthropocentrism and techno-optimism, in which beliefs are differentiated into existence, descriptive, and outcome types. According to their categorization, existence beliefs concern whether something is real or present, descriptive beliefs pertain to its characteristics or attributes, and outcome beliefs relate to the anticipated consequences of actions. In what follows, the constructs of anthropocentrism and techno-optimism are discussed in greater detail.

Techno-optimism

Technology optimism is a belief that reflects individuals' expectations that technology will enhance their control, flexibility, and productivity (Parasuraman, 2000; Danaher, 2022). This belief is one of four key dimensions of the Technology Readiness Index (TRI), alongside innovativeness, discomfort, and insecurity, and represents a general conviction that technology contributes beneficially to daily life and work (Parasuraman, 2000; Colby and Parasuraman, 2001). Colby and Parasuraman (2001) developed a taxonomy of customer segments based on their readiness to adopt technology, categorizing them as explorers, pioneers, skeptics, paranoids, and laggards. This classification reflects a continuum ranging from highly proactive adopters, such as explorers and pioneers, to the most technology-resistant groups, such as paranoids and laggards. Interestingly, Tsikriktsis (2004) found that explorers and pioneers are groups with high optimism, thus it would be a significant predictor of consumers' AI adoption behavior. Thus, techno-optimism is conceptualized as an outcome belief in this dissertation, as it reflects individuals' expectations of positive outcomes from adopting technologies such as medical AI.

Empirical studies consistently find a positive relationship between optimism and the adoption of novel technologies. Gilly et al. (2012) showed that curiosity and proactive coping fostered optimism among older consumers, which in turn predicted internet adoption. Othman et al. (2020) found that optimism shaped satisfaction evaluations of self-service technologies (SSTs), moderating how consumers judged service outcomes. In healthcare, Verma et al. (2025) demonstrated that optimism reduced the negative effects of privacy concerns and tradition-related distrust on elderly consumers' resistance to mHealth apps, suggesting that optimism functions both as a driver of adoption and as a buffer against perceived barriers. This highlights that optimism not only drives adoption intentions directly but also mitigates perceived barriers in sensitive contexts where trust and privacy loom large.

Research on the extension of technology optimism into AI-specific domains has increased in recent years (Lillemäe, Talves and Wagner, 2025). In the context of AI, optimism emerges as a salient predictor of adoption intention. Flavián et al. (2021) showed that optimism significantly increased intention to use robo-advisors, while insecurity reduced it. Interestingly, technological discomfort also positively influenced adoption because AI systems automate tasks, lowering effort barriers. Yang et al. (2025) further demonstrated that optimism surpassed fear of missing out (FOMO) in predicting generative AI adoption: optimistic individuals relied more on positive beliefs about the technology than on affective pressures. More broadly, studies show that optimists not only perceive greater benefits in new technologies (Son and Han, 2011) but also interpret their societal impacts more positively (Álvarez-Marín, Velázquez-Iturbide and Castillo-Vergara, 2023). For example, Hwang and Good (2014) found that optimism predicted stronger adoption intention of intelligent sensor-based services, even when consumers were exposed to negative information.

However, findings are not without inconsistencies. Othman et al. (2020) observed that optimism weakened sensitivity to reliability in SSTs, implying that overly optimistic users may hold unrealistically high expectations that lead to disappointment. Flavián et al. (2021) reported that discomfort, traditionally an inhibitor, could paradoxically encourage adoption in AI contexts, suggesting that optimism interacts with automation design to reconfigure barriers. Similarly, Verma et al. (2025) noted that optimism did not fully overcome privacy and tradition-related barriers in elderly mHealth adoption. These results highlight that the influence of optimism is contingent on context, user characteristics, and the degree of automation involved.

Anthropocentrism

Humans frequently draw a boundary between the ‘self’ and the ‘other,’ whether at the individual or group level, and this occurs both consciously and unconsciously (Havlík, 2019). Such differentiation creates a cognitive frame that privileges the ‘self’ while marginalizing the ‘other’ (Gunaratne, 2009; Weger and Herbig, 2021). In this context, the notion of the ‘other’ extends to both nature and artificial intelligence (AI), reflecting the idea of anthropocentrism within philosophy and AI studies (Nass *et al.*, 1995). Anthropocentrism is a multidimensional psychological belief that reflects the tendency to perceive humans as inherently superior and fundamentally distinct from non-human entities, assigning intrinsic value primarily to human life while treating nature and other non-human agents as instrumental to human ends (Gagnon Thompson and Barton, 1994; Boslaugh, 2016; Fortuna, Wróblewski and Gorbaniuk, 2023).

Anthropocentric people thus view the natural world as existing to serve human needs and that human welfare should take precedence in moral and practical decision-making (Kortenkamp and Moore, 2001). Following Fortuna et al. (2023), anthropocentrism is characterized by perceived human dominance, centrality, and the normative right to exploit non-human entities for human benefit. According to Hayward (1997), anthropocentrism can be divided into two forms: ‘weak’ anthropocentrism, which emphasizes promoting human health, welfare, and prosperity, and ‘strong’ anthropocentrism, which places human interests above all other species and aligns with ideas of human chauvinism and speciesism. Kopnina et al. (2018), however, challenge this separation, arguing that speciesism and human chauvinism are not limited to ‘strong’ anthropocentrism but are inherent to anthropocentrism itself, since it is fundamentally a worldview of human supremacy.

In the domain of human–AI relations, anthropocentrism offers a valuable lens for understanding attitudes and biases toward intelligent systems. Early work on how anthropocentrism affects consumer views of computers was carried out by Nass et al. (1995). The acceptance of technology in human roles refers to the degree to which individuals believe that technological systems can perform tasks traditionally carried out by humans (Nass *et al.*, 1995). Nass et al. (1995) conceptualized this dimension across three domains: routinized roles (e.g., bank tellers), interpretive roles (e.g., editorial writers), and personal roles (e.g., babysitters). Their experiments in the 1990s revealed that people were more comfortable with computers in routinized roles but showed lower acceptance when computers were assigned interpretive or personal roles. For a significant period, research on the role of anthropocentrism in determining consumer adoption of technology has been drought (Shi *et al.*, 2025). However, in recent years, this research area has revived due to the advancement of AI and its increasing integration in human life (Schmitt, 2020; Ikari *et al.*, 2023; Fortuna *et al.*, 2024; Shi *et al.*, 2025). Research by Fortuna (2023; 2024) found a positive association between anthropocentrism and negative attitudes toward robots, with AI anxiety playing a mediating role. Fortuna et al. (2022) also found that anthropocentrism is positively associated with negative attitudes toward robots. They further demonstrated the mediating influence of AI anxiety. Their findings indicate that anthropocentric perspectives shape attitudes toward AI, particularly in more conservative societies where concerns about AI’s potential to disrupt human-dominated domains are prevalent. Their findings suggest that AI anxiety is not simply a response to perceived AI shortcomings but a deeper reflection of the cultural and psychological tensions between

human-centered capability and the rise of AI as an alternative force. These biases and anxieties could be more substantial, especially in healthcare, where people's lives are at stake. In the domain of art, Millet et al. (2023) empirically establish that anthropocentric beliefs, specifically, the conviction that creativity is a unique human faculty, significantly shape aesthetic evaluations of AI-generated artworks. Across four experiments with 1,708 participants, the same artwork was consistently judged as less creative and elicited lower awe when presented as AI-generated rather than human-made. Notably, individuals who endorsed stronger anthropocentric creativity beliefs exhibited a more pronounced devaluation of AI art, including lower aesthetic appreciation and lower purchase intention.

On the other hand, Modliński and Trump (2025) surprisingly found that individuals with speciesist beliefs (a form of anthropocentrism) were particularly receptive to automation in customer service. They argued that this receptivity stems from the perception that certain jobs are “beneath humans” and therefore better suited for machines. In this light, speciesists valued automation for its capacity to relieve humans of mundane or illegitimate tasks. Empirical support for this claim came from their observation of a positive correlation between speciesism and the perception that customer service automation is justified, as well as more favorable attitudes toward brands employing automated services, particularly when speciesists considered their own work tasks to lack legitimacy. In the healthcare domain, Huo et al. (2024) found that patients with stronger specism showed lower acceptance of medical AI when positioned in an independent role, but higher acceptance when AI functioned in an assistive role. Their study further demonstrated the mediating role of human–computer trust and the positive moderating effect of perceived human uniqueness on the relationship between speciesism and trust in AI. However, Huo et al.’s (2024) mainly examined speciesism; thus, an analysis on a broader construct of anthropocentrism is still necessary to capture the wider spectrum of human-centered beliefs and their influence on attitudes toward AI in different roles. Moreover, their findings invite further investigation into the cognitive processes through which anthropocentrism influences acceptance of AI in assistive versus independent roles.

In the domain of healthcare, Shi et al. (2025) revisit the construct of anthropocentrism in the context of contemporary AI use for health-related information seeking, extending the classic “Computers Are Social Actors” (CASA) paradigm to a “Media Are Social Actors” (MASA) framework. They conceptualize anthropocentrism through three dimensions, physical anthropomorphism, psychological

anthropomorphism, and acceptance of AI in human roles (routinized, interpretive, and personal), to examine how these dimensions shape user profiles in AI adoption. They conducted a study to understand the behavioral underpinnings of users adopting AI for health information seeking, employing a quota-sampled survey with 1051 AI-experienced users in Hong Kong. Shi et al. (2025) found five distinct user profiles: Discreet Approachers, Casual Investigators, Apprehensive Moderates, Apathetic Bystanders, and Anxious Explorers. Each is associated with specific demographic factors, perceptions, and different aspects of anthropocentrism, including physical anthropomorphism, psychological anthropomorphism, and the acceptance of AI in routinized, interpretive, or personal roles. Individuals exhibiting higher levels of anthropocentrism (i.e., a stronger orientation toward human centrality over non-human agents) were more likely to belong to profiles such as Apprehensive Moderates, Apathetic Bystanders, and Anxious Explorers, which are characterized by lower trust in AI tools. In contrast, profiles with weaker anthropocentric tendencies, such as Discreet Approachers and Casual Investigators, demonstrated greater openness to AI as a health information-seeking resource. The findings of Shi et al. (2025) demonstrate that anthropocentric consumers are not strictly opposed to AI in healthcare; rather, they may accept it in certain roles, as reflected in profiles such as Discreet Approachers and Casual Investigators. By contrast, other profiles (e.g., Apprehensive Moderates, Apathetic Bystanders, and Anxious Explorers) remain more reluctant, particularly when AI is applied in interpretive or personal roles. As Nass et al. (1995) classified, the role of the doctor often falls within these categories, since diagnosis and care require judgment, analysis, and specialized expertise, as well as empathy and relational trust.

Therefore, in this dissertation, anthropocentrism is examined for two main reasons. First, the influential findings of Nass et al. (1995) on anthropocentrism are now nearly three decades old (Shi *et al.*, 2025). Since then, the rapid evolution of AI-based technologies, such as smartphones, chatbots, large language models, and recommendation systems, may have significantly reshaped how users perceive and respond to technology (Gambino, Fox and Ratan, 2020). As a result, acceptance of AI in social roles may also have been reconfigured, making it timely to revisit how anthropocentrism influences consumers' intention to adopt AI, especially in a high-stakes context such as healthcare. Second, prior studies have largely conceptualized anthropocentrism in contexts where AI is positioned as a replacement for humans, while its impact on adoption when AI is framed in an assistive role has received less attention, except for Huo et al. (2024). When AI is presented as a substitute for human doctors, it

is reasonable to expect that anthropocentric consumers, those with a strongly human-centered worldview, would resist attributing human qualities or tasks to AI. Conversely, when AI is embedded in a system and framed as an assistive tool, anthropocentric consumers may not exhibit the same bias toward AI, and could be more receptive due to its utilitarian benefits. According to Huo et al. (2024), the direct effects of specism on acceptance of medical AI remained significant even after incorporating human–computer trust as a mediator, suggesting that additional unexplored mediating mechanisms may be at play. Therefore, this dissertation posits that there is a cognitive mechanism through which anthropocentrism influences behavioral intention, potentially differing from the conventional view of its direct effect on attitudes or intentions. In addition, Shi et al. (2025) found that consumers with anthropocentric beliefs would accept AI differently depending on their consumer profiles, which are characterized by their perceptions and attributes. Thus, this dissertation posits that there is a range of factors that contribute to reasons for and against the adoption of medical AI by consumers.

1.1.4. Research gaps

Despite the growing body of research on artificial intelligence (AI) adoption across sectors, several limitations persist in the extant literature, particularly regarding the healthcare context. First, many studies have primarily focused on technological and utilitarian factors such as perceived usefulness, ease of use, or performance expectancy, as emphasized in models like TAM, UTAUT, or TPB (Dwivedi *et al.*, 2021; Khanijahani *et al.*, 2022). While these frameworks offer valuable insights, they often neglect deeper psychological factors that may motivate or inhibit consumers' use of novel technologies (e.g., AI), such as beliefs. Previous research on AI and algorithmic advice has yielded inconsistent findings. Some studies highlight consumer resistance, often referred to as algorithm aversion. For instance, Dietvorst et al. (2015) found that individuals were less likely to rely on algorithmic predictions after observing an error, even if the algorithm outperformed human judgment. In healthcare, Promberger and Baron (2006) and Longoni et al. (2019) observed a lack of trust in medical AI, partly due to concerns that it ignores human uniqueness. Similarly, Castelo et al. (2019) showed that aversion is stronger for intuitive tasks compared to objective ones. In contrast, other studies report positive responses. Logg et al. (2019) found that people often preferred algorithmic advice over human input in domains like forecasting and decision-making, while Hildebrand and Bergner (2021) noted increased appreciation when AI communicated in a human-like style. These conflicting outcomes suggest that

additional underlying factors, such as beliefs, may significantly influence AI adoption. Indeed, von Walter et al. (2022) examined how lay beliefs about AI, defined as individuals' subjective and informal understandings of complex phenomena such as health, illness, and technology that may diverge from expert or scientific knowledge, affect the adoption of algorithmic investment advisors. Across three experimental studies, they found consistent evidence that consumers who believe AI possesses superior intelligence to humans are more inclined to adopt algorithmic advice. Furthermore, their findings revealed that these lay beliefs significantly influence adoption only when the decision task is perceived as complex. While this research highlights the role of lay beliefs in shaping adoption decisions, it also raises important questions about other belief systems that may affect consumers' adoption of AI. Prior studies have identified the role of competing worldviews, such as the lay belief that AI exceeds human intelligence or, conversely, that humans remain inherently superior. In addition to the scarcity of research on lay beliefs in the context of AI adoption (Huang and Rust, 2018), limited attention has been paid to the role of other beliefs, such as anthropocentrism (that is, the belief in human exceptionalism) or techno-optimism (the belief that emerging technologies like AI can contribute positively to human progress). The potential influence of these belief dimensions on AI adoption remains underexplored, representing a critical gap in the literature.

Second, an emerging gap is the mechanism via which belief influence behavior (Granados Samayoa and Albarracín, 2025). They suggest that there is limited attention given by researchers to the mechanisms linking beliefs to behavior stems from the orientation of earlier models. Despite widespread intuition among both laypersons and psychologists that beliefs are powerful behavioral drivers, empirical evidence consistently shows that the actual association between beliefs and behaviors is often small and highly variable, typically with correlations below $r = .2$ (Granados Samayoa and Albarracín, 2025). Previous behavioral intention theories, such as the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), have primarily focused on predicting behavior using global measures of attitude, subjective norms, and perceived control, largely overlooking the detailed cognitive processes linking specific beliefs to actions and the context-specific beliefs that are crucial for understanding behavioral origins and change mechanisms (Sahu, Padhy and Dhir, 2020; Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025). This oversimplification has often led to the incorrect assumption of a strong, direct influence of beliefs on behavior. Thus, scholars have argued that earlier theories fall short in uncovering the cognitive mechanisms and contextual conditions through which beliefs influence behavior

(Albarracín and Wyer Jr., 2001; Albarracín, 2002). Addressing this gap, Samayoa and Albarracín (2025) argue that a belief must be connected to a reasoning process, termed *belief-to-behavior inference*, for it to exert a causal impact. This approach highlights an underexplored cognitive mechanism that clarifies why some beliefs shape behavior while others remain inert. Thus, this research aims to address this gap by employing a suitable theoretical lens, such as Behavioral Reasoning Theory, as Westaby (2005; 2025) consistently advocated that BRT was an appropriate model to study the role of beliefs and its impact mechanism.

Third, in terms of geography, most empirical studies have been conducted in high-income Western countries, with limited attention given to emerging markets such as Vietnam and other low- and middle-income countries (LMICs) (Jain, Wadhwani and Eastman, 2024). This represents a significant limitation, as consumers in transitional economies like Vietnam are situated at the intersection of deep-rooted traditions and an increasing influx of Western cultural influences and products (Nguyen, Smith and Cao, 2009; Nguyen *et al.*, 2019). Such dynamics can create tensions in perceptions and pose challenges for the adoption of novel technologies, particularly medical AI, which has the potential to reshape conventional models of healthcare delivery. Examining consumer adoption of medical AI in developing countries outside China is therefore crucial, as it can reveal context-specific beliefs and factors that remain overlooked in the existing literature.

1.2. Theoretical framework and hypotheses

1.2.1. Behavioral Reasoning Theory

Previous research on technology adoption has widely employed established theoretical frameworks such as the Technology Acceptance Model (Davis, 1989), Theory of Planned Behavior (Ajzen, 1991), and Unified Theory of Acceptance and Use of Technology (Venkatesh, Thong and Xu, 2012). These models primarily emphasize attitudinal factors, perceived ease of use, perceived usefulness, and social influences, providing robust explanations for individual intentions to adopt technology. However, these theories often incorporate positive factors without incorporating negative factors into their framework (Li and Wang, 2024). Additionally, individuals often have different reasons for considering whether to perform the target behavior. Also, new technology often encounters resistance from consumers. Thus, underlying cognitive reasoning processes should not be overlooked when examining antecedents of consumers' behavior, particularly, their reasons for

and against adopting technology (Westaby, 2005; Claudy, Garcia and O'Driscoll, 2015). Behavioral Reasoning Theory (BRT) offers a valuable framework for unpacking the reasons for and against adoption by capturing individual beliefs, values, and contextual influences (Lalicic and Weismayer, 2021; Zhang, Bai and Ma, 2022).

Overview of Behavioral Reasoning Theory

BRT introduced by Westaby (2005), extends traditional cognitive models of decision-making by emphasizing the role of reasons for and reasons against a particular behavior. Unlike models such as the Theory of Planned Behavior (TPB), which focus primarily on global psychological constructs such as attitude, subjective norm, and perceived behavioral control, BRT posits that people form behavioral intentions based on concrete, context-specific reasons that both precede and mediate the effects of values, beliefs, and global motives. Reasons for behavior reflect motivations or justifications that support action, while reasons against highlight barriers or concerns that discourage it. BRT recognizes that individuals often hold conflicting cognitions simultaneously, and that these competing rationales can have differential impacts on intention formation. The model has gained traction across domains such as consumer behavior, sustainability, and health technology adoption.

The constructs within the BRT are defined as follows. Beliefs or values are conceptualized as cognitive structures or subjective probability assessments influencing an individual's anticipated appropriate behaviors in future contexts (Fishbein and Ajzen, 1975). BRT posits that values/beliefs underpin behavioral intentions, influencing how individuals interpret and rationalize expected behaviors (Westaby, 2005). When encountering uncertainty, individuals assess their values in relation to potential behavioral options (Claudy, Garcia and O'Driscoll, 2015). Throughout this evaluative process, individuals seek legitimate reasons that uniquely explain their choices, serving as justification and supporting rationalization for their behavioral decisions (Westaby, Probst and Lee, 2010; Claudy and Peterson, 2014). Reasons encompass the diverse justifications, both for and against undertaking specific behaviors (Westaby, 2005).

Global motives consist of three sub-components: attitudes (ATT), subjective norms (SN), and perceived behavioral control (PBC) (Ajzen, 1991). ATT denotes the overall evaluative judgment toward performing a particular behavior, derived from reflective and analytical reasoning (Fishbein and Ajzen, 1975). Intention to use (IU) describes an individual's inclination or willingness to initiate and sustain efforts to

execute the behavior (Ajzen, 1991) . Finally, user behavior signifies the actual performance or enactment of the intended action.

Within BRT, beliefs are understood as fundamental antecedents that inform the subjective reasons individuals provide to justify or defend their intended actions (Westaby, 2005). These reasons (i.e., reasons for and against) are central to shaping global motives such as attitudes, subjective norms, and perceived behavioral control, which then influence intentions and ultimately behavior (Westaby, 2005; Westaby, Probst and Lee, 2010). Recently, Westaby (2025) argues that reasons serve not merely as explanatory factors but as practical cognitive mechanisms through which belief systems are activated, filtered, and transformed into motivational reasoning.

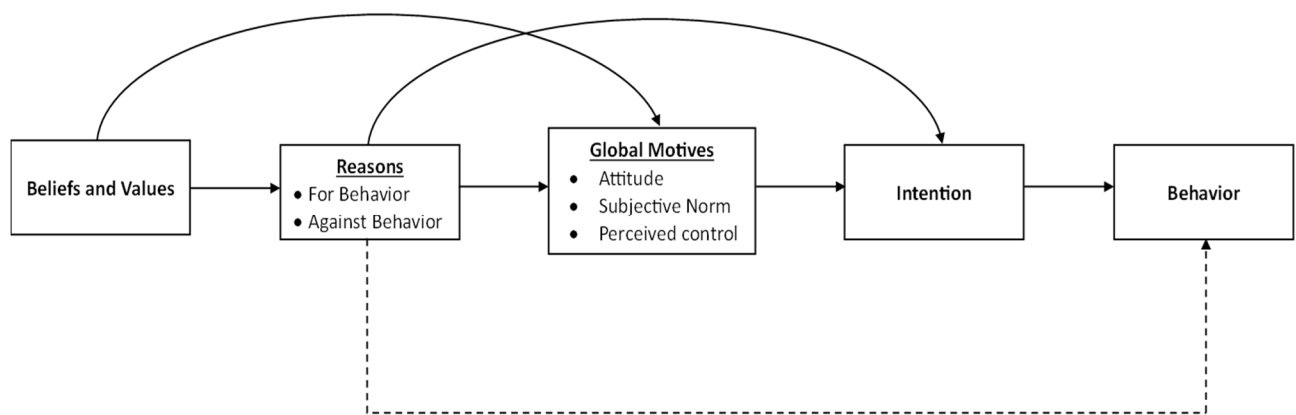


Figure 1.3. Behavioral Reasoning Theory

Source: Westaby (2005)

Several theoretical perspectives converge on the notion that reasons are central determinants of behavior. Explanatory models argue that people evaluate decision alternatives based on the coherence and plausibility of the reasons supporting them, which enhances confidence in their choices (Pennington and Hastie, 1988, 1992, 1993). Similarly, reasons theory posits that reasons not only motivate action but also provide justification and self-validation, thereby protecting self-worth (Kunda, 1990; Westaby and Fishbein, 1996; Westaby, 2005). Research further suggests that reasons guide the pursuit of goals (Bagozzi, Bergami and Leone, 2003). Also, behavioral change efforts are effective only when they address the specific functions or reasons underlying the behavior (Katz, 1960).

Within the framework of BRT, Westaby (2005, p. 100) defined reasons as the “specific subjective factors people use to explain their anticipated behavior”, which serve as antecedents to both attitudes and intentions (Westaby, 2005; Claudy, Peterson and O’Driscoll, 2013). Put differently, reasoning represents the cognitive process

through which individuals decide on a particular course of action (Ryan and Casidy, 2018, p. 240). The literature further indicates that reasons encompass two key sub-dimensions: reasons for (RF) and reasons against (RA) a given behavior (Westaby, Probst and Lee, 2010; Sivathanu, 2018). Following Westaby (2005), *reasons for* refer to the specific subjective justifications individuals use to support engaging in a particular behavior, such as perceived facilitators or benefits, whereas *reasons against* denote the subjective justifications used to oppose or avoid a behavior, including perceived constraints or barriers. Importantly, BRT suggests that individuals may simultaneously hold reasons for and reasons against a behavior, which function as opposing but distinct motivational forces rather than as opposite ends of a single evaluative continuum (Westaby, 2005). This conceptualization aligns with psychological models of decision making that emphasize the coexistence of competing motivational forces in behavioral choice (Roe, Bussemeyer and Townsend, 2001). Within this framework, reasons are designed to capture a broad and context-specific explanation set, reflecting the fact that individuals often rely on multiple justifications to explain or rationalize their behavior (Westaby, 2005). Prior research has operationalized such opposing justifications using various labels, including pros versus cons, benefits versus costs, and facilitators versus obstacles or barriers, underscoring their conceptual independence (Westaby and Fishbein, 1996; Westaby, 2005; Westaby, Probst and Lee, 2010). Moreover, context-specific reasons provide a structured lens for understanding both adoption and resistance by capturing self-justification and defensive reasoning processes that are often overlooked in more global attitudinal models (Chatzidakis and Lee, 2013). Consistent with Behavioral Reasoning Theory (Westaby, 2005), this study conceptualizes reasons for adoption and reasons against adoption as context-specific, cognitive justifications that individuals use to explain, support, or oppose a focal behavior. Unlike belief-based constructs such as perceived usefulness or perceived risk, reasons are not evaluations of attributes per se, but articulated rationales that translate underlying beliefs and values into attitudinal judgments and behavioral intentions (Westaby, 2005, pp. 7–8; Claudy, Peterson and O’Driscoll, 2013, pp. 276–277). As such, reasons for and reasons against function as theoretically distinct motivational constructs that mediate the effects of beliefs on global motives and intention, rather than as simple proxies for benefits or risks. Following prior BRT-based studies, reasons for and reasons against are operationalized as formative second-order constructs, composed of multiple context-specific first-order dimensions that collectively capture consumers’ articulated justifications supporting or opposing healthcare AI adoption (Li and Wang, 2024;

Ahmad and Harun, 2023; Ashfaq *et al.*, 2021; Claudy, Garcia and O'Driscoll, 2015; Claudy and Peterson, 2014; Claudy, Peterson and O'Driscoll, 2013). Prior BRT research has consistently conceptualized reasons as aggregations of specific justifications whose content varies across behaviors and contexts (Westaby, 2005; Claudy, Peterson and O'Driscoll, 2013; Claudy, Garcia and O'Driscoll, 2015; Li and Wang, 2024). Accordingly, the specific dimensions underlying reasons for and reasons against were elicited through an exploratory qualitative phase to ensure contextual relevance.

Researchers have employed this framework to investigate consumer behavior in contexts such as sustainable transportation choices, including bicycle commuting (Claudy and Peterson, 2014), innovation resistance (Claudy, Garcia and O'Driscoll, 2015), mobile shopping (Gupta and Arora, 2017), and AI chatbot adoption of employees at the workplace (Pillai *et al.*, 2023). In the travel sector, Lalicic and Weismayer (2021) found that consumers' personal values, mediated by both supportive and inhibiting reasons, significantly predicted intentions to use AI-enabled travel service agents. Extending BRT to mobility technology, Huang and Qian (2021) surveyed 849 Chinese consumers and showed that reasons for adopting autonomous vehicles exerted a positive effect on intention, while reasons against exerted a negative one; moreover, psychological traits such as need for uniqueness strengthened positive pathways, whereas risk aversion amplified negative pathways, highlighting how individual differences shape the reasoning–intention link. Li and Wang (2024) examined 604 prospective users of AI-assisted diagnostic systems and demonstrated that the personal value of openness to change influenced both supportive and inhibiting reasons, which in turn affected attitudes and ultimately adoption intention. Although BRT has been applied in numerous studies to explore factors influencing AI adoption across various contexts, most have primarily emphasized the role of values in shaping consumers' cognitive reasoning and subsequent behavioral intentions. However, as originally proposed by Westaby (2005), beliefs also serve as critical antecedents of reasons. This dimension has often been underexamined, leaving a notable theoretical gap in the application of BRT to technology adoption.

Reasons to use Behavioral Reasoning Theory

BRT offers a compelling framework to investigate further the Belief-to-Behavior Inference (BBI) model introduced by Granados Samayoa and Albarracín (2025), addressing a shared acknowledgment of the need for a deeper understanding of how and when specific beliefs influence behavior (Granados Samayoa and Albarracín, 2025;

Westaby, Rosemarino and Elliot, 2025). While traditional theories like the TRA and TPB have focused on global measures of attitudes, subjective norms, and perceived control, they often overlook the context-specific beliefs and reasons that are crucial for behavioral mechanisms (Westaby, Probst and Lee, 2010; Sahu, Padhy and Dhir, 2020; Westaby, Rosemarino and Elliot, 2025). Integrating BRT into technology adoption research thus enables a more profound and better understanding of decision-making processes, capturing both supportive and opposing considerations simultaneously (Ryan and Casidy, 2018). Hence, employing BRT offers a significant theoretical advancement by addressing gaps unaccounted for in TAM, TPB, and UTAUT, thereby enriching predictive power and practical relevance in technology adoption studies (Claudy, Garcia and O'Driscoll, 2015; Gupta and Arora, 2017).

BRT emphasizes explicitly the role of *reasons for* and *reasons against* a behavior, which are distinct, context-specific cognitive routes that provide richer information for predicting intentions and actual behavior than global motives alone (Claudy, Garcia and O'Driscoll, 2015; Sahu, Padhy and Dhir, 2020). This aligns with the BBI model's call for research into "practical reasoning" that underlies behavioral formation (Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025), which BRT posits can be explored through a "multifaceted BRT" (MBRT) approach that incorporates primary reasoning, counter-reasoning, and comparative reasoning facets (Westaby, Rosemarino and Elliot, 2025). Such an integration could provide new insights into how individuals process decision attributes and beliefs, bridging the gap between specific beliefs and their direct impact on behavior or intentions, while also considering recursive effects where behavior influences beliefs (Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025).

Furthermore, BRT's established emphasis on salience, where a smaller set of primary reasons emerges from a larger constellation of beliefs and becomes more influential in decision-making, resonates with BBI's conceptualization of salience as an important explanatory factor (Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025). The BBI model's typology of existence, descriptive, and outcome beliefs could also be integrated into BRT to examine the impact of different types of beliefs on consumers' rationales, hence their behavioral intention (Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025). Specifically, this dissertation conceptualizes anthropocentrism and techno-optimism respectively as a descriptive belief and an outcome belief.

1.2.2. Impact of attitude on intention to adopt medical AI

Attitude has long been recognized as a central determinant of behavioral intention across multiple theoretical frameworks, including the TRA, TPB, and the UTAUT (Fishbein and Ajzen, 1975; Venkatesh, Thong and Xu, 2012). BRT maintains this core relationship by positing that a positive global attitude toward a behaviour directly strengthens the intention to perform it (Westaby, 2005). In the context of healthcare technology, extensive research has validated this positive association (Li and Wang, 2024). In general, AI adoption behaviors are like the other types of novel technology adoption that focus on consumers' attitudes and knowledge. For example, Nadarzynski et al. (2019) found that consumers who are curious and have a positive attitude toward the new technology are the most likely to accept AI-powered chatbots. In the healthcare context, consumers' evaluations of the technology in question play a central role in determining subsequent adoption behavior. In this regard, Deng et al. (2014) found that young and older consumers tend to adopt mobile health services that they rated favorably. In China, consumers with favourable attitudes toward medical AI were more inclined to adopt it (Li and Wang, 2024). Given the nascent stage of the adoption of medical AI in Vietnam, empirical evidence on consumer adoption of this technology remains limited. Nevertheless, it is posited that Vietnamese consumers' adoption intentions will follow similar patterns to those identified in previous studies, with more positive attitudes leading to stronger intentions to adopt AIMDSS. Thus, the author proposes the following hypothesis:

H1. Users' attitude toward AIMDSS will positively influence their intention to adopt AIMDSS

1.2.3. Impact of reasons on intention to adopt medical AI

The use of the BRT model helps introduce reasons into the examination of factors influencing consumers' intention to adopt AIMDSS. Synthesized from established research, studies show that consumers are likely to adopt alternatives supported by coherent, plausible, and strongly justified reasons, thereby enhancing decisional confidence (Pennington and Hastie, 1993; Westaby, 2005). Further, examining reasons helps clarify how consumers justify and defend their adoption decisions, thereby reinforcing their sense of self-worth and confidence (Tetlock, Skitka and Boettger, 1989; Kunda, 1990; Westaby and Fishbein, 1996). Also, justifiable reasons guide consumers toward clearly defined adoption goals, facilitating more deliberate decision-making processes (Gigerenzer and Goldstein, 1996; Bagozzi, Bergami and Leone, 2003).

Additionally, reasons serve an instrumental role in helping consumers cognitively interpret and rationalize their environment by offering causal explanations for their own and others' behaviors, thus reducing uncertainty and promoting a clearer understanding of product/service adoption decisions (Westaby, 2005). Collectively, these advantages underscore the importance of explicitly incorporating reasons into analyses of the antecedents of AIMDSS adoption. Given the novelty of AIMDSS, the high-risk healthcare context, and the relatively early stage of its adoption in a developing country like Vietnam, there is a clear need to examine further the specific reasons underlying consumers' intentions to either adopt or resist such innovative technology.

According to Westaby (2005), reasons are defined as specific subjective factors individuals rely on to justify and explain their intended behavior. The BRT framework further posits that reasons comprise two sub-dimensions: *reasons for* and *reasons against*. Further, reasons can portray not only people's pros/cons and benefits/costs explanations, but also their facilitators/constraints explanations. Empirical studies applying BRT have demonstrated that reasons for adoption are a significant positive predictor of behavioural intention. For example, in the context of adopting radical new technologies, reasons for adoption directly and positively influenced adoption intentions (Claudy, Garcia and O'Driscoll, 2015). Similarly, when examining mobile health services, Lee et al. (2023) found that reasons for adoption, such as relative advantage, compatibility, and perceived threat severity, directly increased users' intention to use the service. In the chatbot domain, Jan et al. (2023) also found that *reasons for* (i.e., perceived convenience, perceived interactivity, and perceived ubiquity) positively affect users' intention to use the agent. However, studies of Claudy (2013) and Claudy (2015) both reported no significant impact of reasons for on adoption intention of consumers in the domain of new product and services adoption. Hence, this dissertation posits that consumers may adopt AIMDSS for several reasons, including their initial trust, personal innovativeness in the domain of health technology, and modern self. Accordingly, this relationship warrants further examination, leading the author to propose that:

H2. Users' *reasons for* adopting AIMDSS will positively influence their intention to adopt AIMDSS

Research applying BRT has consistently found a significant negative relationship between *reasons against* and intention (Westaby, 2005; Claudy, Garcia and O'Driscoll, 2015; Pillai *et al.*, 2023). In the AI adoption domain, Jan et al. (2023) found that reasons against had a positive impact on users' resistance to adopting an AI-powered chatbot. In

the context of AIMDSS adoption in Vietnam, consumers may form reasons against based on two core components: traditional self and perceived threats. Individuals with a strong traditional self may express skepticism about replacing human expertise with algorithmic decision-making or prefer conventional face-to-face consultations over machine-supported diagnostics. Meanwhile, perceived threats, including identity-based concerns such as fear that AI undermines the human element in healthcare, and realistic concerns such as diagnostic errors, data misuse, or job losses in the medical sector, can reinforce psychological resistance. These reflective dimensions collectively form the higher-order *reasons against* construct, which serves as a proximal barrier to the adoption of AIMDSS. Therefore, the author proposes that:

H3. Users' *reasons against* adopting AIMDSS will negatively influence their intention to adopt AIMDSS

1.2.4. Impact of reasons on attitude toward medical AI

Within BRT, *reasons for* a behavior represents contextual justifications that mediate the influence of belief systems on global evaluative constructs such as attitudes (Westaby, 2005). Empirical evidence across different domains supports the assertion that positive reasoning enhances attitudes. For example, in sustainability contexts, Claudy et al. (2013) demonstrated that reasons for adoption positively influence attitudes toward green energy products, reinforcing that reasoned justifications serve as cognitive antecedents to attitudinal alignment. In healthcare settings, Li and Wang (2024) found that reasons for (i.e., initial trust, health information accessibility, professional level, and perceived informational support) positively affect the attitude of consumers toward AIMDSS in China. Thus, the author proposes that:

H4. Users' *reasons for* adopting AIMDSS will positively influence their attitudes toward AIMDSS

Conversely, *reasons against* a behaviour provides the cognitive basis for an unfavourable evaluation. When potential users in Vietnam evaluate the downsides of AIMDSS, such as its potential to undermine the traditional human-centered care, replace traditional doctor–patient interactions, disrupt familiar healthcare routines, or challenge deeply rooted norms about human expertise in medicine, these concerns would be more robust in those who identify themselves as traditional. Nguyen et al. (2009) suggested that consumers who embrace traditional self are more risk-averse and cautious about trying new products/services. Additionally, perceived threats, comprising identity threat (e.g., fears that AI compromises the personal and humanized nature of care) and realistic

threat (e.g., concerns over diagnostic errors or job displacement), further reinforce negative appraisals (Huang *et al.*, 2021). However, evidence on the relationship between reasons against and attitude has been mixed. There was some confirmed negative relation in the medical AI adoption domain (Pillai *et al.*, 2023; Li and Wang, 2024), while a non-significant effect of this relation was also reported (Claudy, Peterson and O'Driscoll, 2013; Jan, Ji and Kim, 2023). As posited by Behavioral Reasoning Theory, these belief-driven justifications serve as proximal cognitive mechanisms that shape users' negative attitudes toward adoption (Westaby, 2005). Thus, in this dissertation, the author would re-evaluate this relation and propose that:

H5. Users' *reasons against* adopting AIMDSS will negatively influence their attitudes toward AIMDSS

1.2.5. Impact of beliefs on consumers' reasons and attitude toward medical AI adoption

1.2.5.1. Impact of technology optimism

Aligning with Samayoa and Albarracín's (2025) proposed belief categorization, technology optimism would be classified as an outcome belief, a judgment of the probability that technology produces a good outcome for the users. Within BRT, this type of belief serves as a foundation for forming 'reasons for' adoption, guiding how individuals justify their support for the behavior and shaping their attitudes and intentions. Empirical studies consistently show that technology optimism is a strong predictor of favorable attitudes, higher perceived usefulness, and adoption behaviors across diverse contexts, including smart environments, e commerce platforms, complex information systems, and AI (Tsikriktsis, 2004; Lin and Hsieh, 2007; Flavián *et al.*, 2021). In the domain of AI, early evidence indicates that students with higher technology optimism show greater perceived ease of use, perceived usefulness, and perceived enjoyment, thus having higher usage intentions (Cui, 2025). Additionally, Jan et al. (2023) found that techno-optimism (as a motivator) positively influences Korean users' reasons for using the AI-powered chatbot. However, an examination of the impact of techno-optimism on reasons against and attitude was not conducted (Jan, Ji and Kim, 2023). Given the limited research on how beliefs influence reasons for and against adoption (Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025), together with the nascent stage of medical AI adoption in Vietnam, further qualitative exploration of the link between technology optimism and reasons for or against adopting

medical AI is needed. Thus, these links would be further specified in the qualitative analysis. Therefore, at this stage, the author proposes that:

H6. Techno-optimism will be related to *reasons for* AIMDSS adoption

H7. Techno-optimism will be related to *reasons against* AIMDSS adoption

Optimism refers to a positive view of technology, including customers' perceptions of control, flexibility, convenience, and efficiency (Parasuraman, 2000). Meta-analytic evidence shows that the optimism facet of Technology Readiness reliably enhances attitudes and downstream usage intentions across settings, implying a robust cognitive-affective pathway from optimism to favorable evaluations (Blut and Wang, 2020). Liljander et al. (2006) found a positive association between consumers' technology optimism and their attitude toward using novel technologies, such as self-service airline check-in. Thus, in healthcare settings, techno-optimism is expected to foster receptivity toward medical AI, especially when such systems are presented as supportive aids that enhance clinicians' work rather than substitutes, and when human oversight remains evident. Thus, the author proposes that:

H8. Techno-optimism will be positively related to attitude toward AIMDSS

1.2.5.2. Impact of anthropocentrism

In this research, anthropocentrism is conceptualized as a descriptive belief, consistent with the definition proposed by Samayoa and Albarracín (2025), which defines it as a judgment about the probability that an entity possesses a certain quality. In this case, it refers to the perceived superiority and centrality of humans relative to non-human agents. This belief reflects a worldview in which human interests are paramount, and nature, animals, or artificial agents are instrumentalized to serve those interests. Empirical evidence suggests that anthropocentric consumers tend to express negative attitudes toward autonomous agents, such as AI (Fortuna, Wróblewski and Gorbaniuk, 2023). Thus, the author would expect resistance or negative attitudes from consumers when AI is positioned as a replacement for them in specific tasks. Such resistance could be driven by concerns about the erosion of human uniqueness and fears of being substituted, which have been suggested by Longoni(2019). These reactions are consistent with intergroup bias theory, which posits that individuals tend to categorize AI as an out-group entity that lacks shared human characteristics and goals (Haslam, 2006). In such contexts, AI systems are perceived as alien agents, triggering psychological discomfort and defensive responses due to their symbolic challenge to human identity and control (de Graaf, Allouch and Klamer, 2015; Złotowski,

Yogeeswaran and Bartneck, 2017). The perceived blurring of boundaries between humans and machines often evokes discomfort, especially when AI systems are seen as capable of replicating complex cognitive or social functions (Złotowski, Yogeeswaran and Bartneck, 2017). As a result, users may begin to question their own distinctiveness and irreplaceability (Ferrari, Paladino and Jetten, 2016).

However, when AI is framed as a supportive tool that assists human users rather than replacing them, especially in settings emphasizing human oversight, consumer receptivity tends to improve (Longoni, Bonezzi and Morewedge, 2019). Still, research by Longoni (2019) mainly addresses the impact of uniqueness neglect; thus, evidence on the impact of anthropocentrism on medical AI adoption by consumers in healthcare is limited. Given the limited empirical evidence on belief–reason linkages (Westaby, Rosemarino and Elliot, 2025) and the nascent state of medical AI adoption in a transitional, developing context such as Vietnam, hypotheses 9 and 10 are therefore proposed as non-directional. Consistent with BRT, the influence of beliefs on reasons is context-dependent and shaped by the justificatory logic consumers employ when explaining their behavioral intentions (Westaby, 2005; Westaby, Rosemarino and Elliot, 2025). Accordingly, a qualitative phase is necessary to elucidate how these beliefs translate into reasons for and reasons against medical AI adoption in the Vietnamese healthcare context. Thus, H9 and H10 are proposed as follows, and will be further specified after the qualitative phase.

H9. Anthropocentrism will be related to *reasons for* AIMDSS adoption

H10. Anthropocentrism will be related to *reason against* AIMDSS adoption intention

Regarding the relationship between anthropocentrism and attitude, empirical studies often examine this link from the perspective that machine can replace human in certain tasks. When AI is portrayed as a substitute for human professionals in high-stakes, interpretive, or care-laden roles, anthropocentric audiences often register identity and agency threat, algorithm aversion, and moral unease, dampening attitudes (Dietvorst, Simmons and Massey, 2015; Bigman and Gray, 2018; Castelo, Bos and Lehmann, 2019; Cave, Coughlan and Dihal, 2019; Longoni, Bonezzi and Morewedge, 2019). Further, a negative association between anthropocentrism and attitudes toward AI powered robot was documented by Fortuna et al. (2024). However, anthropocentrism does not inherently imply rejection of AI; rather, it reflects a belief in the centrality of humans.

When AI is explicitly framed as a supportive decision tool that preserves human oversight and accountability, anthropocentric individuals may respond more favorably,

as such systems align with their expectation that humans remain in control. Prior research shows that acceptance of medical AI improves when AI is positioned as augmenting rather than replacing clinicians (Longoni, Bonezzi and Morewedge, 2019). This suggests that when AI is explicitly positioned as a clinician support tool that preserves human oversight, accountability, and discretion, anthropocentrism can be associated with more favourable attitudes. In the context of AIMDSS adoption, AI functions as a human-in-the-loop technology designed to extend clinical competence, enhance performance, and stabilize trust through physician mediation, explainability, and governance safeguards (Logg, Minson and Moore, 2019; Fan *et al.*, 2020; Li and Wang, 2024). Under these conditions, anthropocentrism may foster positive attitudes toward AI adoption, as the technology is perceived as reinforcing rather than undermining human authority. Accordingly, this study proposes that:

H11. Anthropocentrism will be positively related to attitude toward AIMDSS adoption.

Based on the BRT and the hypothesis development, the author propose the research framework as depicted in Figure 1.4.

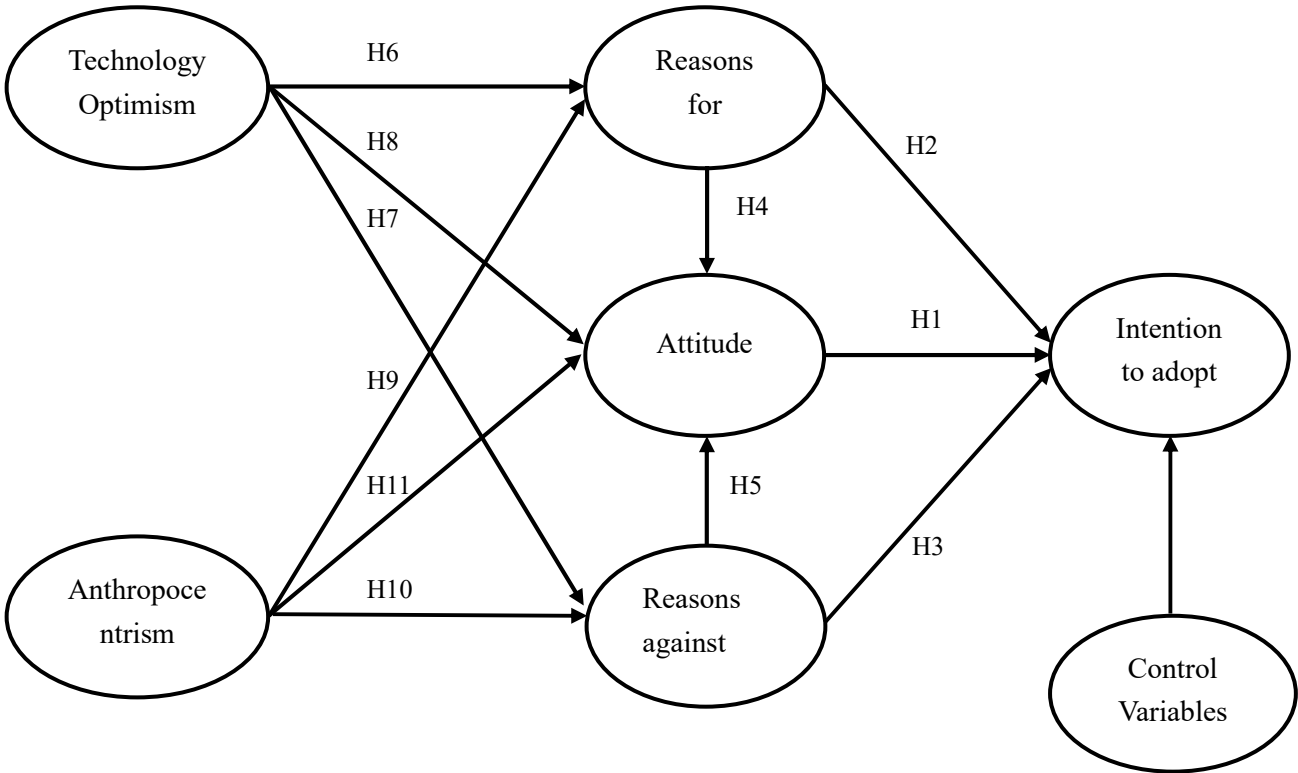


Figure 1.4. Theoretical framework

SUMMARY OF CHAPTER 1

Chapter 1 opens by defining artificial intelligence (AI), emphasizing the unique features that distinguish it from other forms of technology. The author then provides an overview of existing literature on AI adoption in general, as well as within healthcare specifically. This sets the stage for a focused examination of consumer behavior in relation to AI.

The chapter proceeds with a structured synthesis of major research themes concerning consumer behavior in the AI context. This includes a review of theoretical frameworks, methodological approaches, and the antecedents that shape AI adoption. Special attention is given to factors influencing consumers' intention to adopt medical AI, including cognitive beliefs and other enablers or barriers to adoption.

The literature review reveals significant insights, but also highlights several research gaps that have not been thoroughly explored in previous studies. To address these issues, the author proposes a theoretical framework to guide the subsequent research. This framework is carefully selected based on its relevance to the topics discussed and its potential to offer new perspectives on luxury consumption behavior.

The chapter concludes by presenting a preliminary research model outlining the core constructs and hypothesized relationships to be empirically tested. Accompanying this model are research hypotheses derived from the theoretical framework, aiming to explore key determinants of AI adoption, particularly highstake context such as healthcare. These elements establish the foundation for the empirical analysis conducted in subsequent chapters.

CHAPTER 2: RESEARCH METHODOLOGY

2.1. Research context

2.1.1. *The context of Vietnam*

Vietnam represents a critical yet underexplored context for examining consumer adoption of AI in healthcare. As a rapidly developing country undergoing a profound digital transformation, Vietnam faces the dual challenge of accelerating technological adoption while navigating infrastructural, educational, and socio-cultural constraints. Despite governmental support and strategic national programs promoting digital health and AI applications in medicine (Thu, Nguyen and Taylor-Robinson, 2023), empirical research on how end-users, particularly consumers, perceive, accept, or resist medical AI remains limited. This gap is significant, as user acceptance and adoption behaviors are essential for the long-term sustainability and scalability of such technologies (Venkatesh *et al.*, 2003).

Vietnam's population is marked by considerable heterogeneity in digital literacy, particularly between urban and rural areas, which may influence readiness and trust in emerging AI technologies. Cultural attitudes also play a pivotal role, since the collectivist orientation and deep-rooted respect for human-centered care in Vietnam may interact in complex ways with perceptions of automation (Trang, Thang and Vo, 2025), raising questions about anthropocentrism, trust, and perceived threat. At the same time, Vietnam's youthful demographic and growing middle class demonstrate increasing enthusiasm for innovation, aligning with global trends in digital health consumerism.

While existing studies in digital health primarily focus on healthcare professionals or system-level implementation (Thu, Nguyen and Taylor-Robinson, 2023), little is known about how ordinary Vietnamese citizens understand, evaluate, and make decisions about AI-based healthcare solutions. Given that consumer-side adoption is a critical component of successful digital health implementation, this research context offers both practical relevance and theoretical richness. Moreover, with the majority of global AI adoption research situated in developed countries, insights from Vietnam can offer a valuable contribution to the literature by illuminating how beliefs, values, and contextual barriers shape AI adoption in emerging economies.

2.1.2. *AI adoption in Vietnamese healthcare setting*

Vietnam's healthcare infrastructure is increasingly supported by a growing digital foundation, fueled by strong governmental initiatives and strategic policies such as Decision No. 749/QĐ-TTg and Decision No. 5349/QĐ-BYT, which promote digital

transformation and the implementation of electronic health records (Ministry of Health, 2019; The Prime Minister, 2020). The widespread adoption of internet connectivity, mobile smart devices, and cloud technologies has further enabled real-time data sharing and access, creating a more responsive and scalable environment for healthcare service delivery. Further, Vietnam has made notable strides in expanding its digital healthcare infrastructure, with cloud-based services enabling innovative, cost-effective solutions and 4G networks, supporting the integration of telemedicine, remote monitoring, and AI-enabled tools (KPMG and Oxford University Clinical Research Unit, 2020). Despite these advancements, Vietnam's healthcare system continues to face significant challenges as a developing middle-income country. With approximately 12.5 physicians per 1,000 people, Vietnam's doctor-patient ratio is relatively low in Asia (Le, 2024). Large public hospitals in Vietnam frequently experience overcrowding, leading to excessive wait times and staff burnout (Nguyen *et al.*, 2018; Quan and Taylor-Robinson, 2022). A cross-sectional survey in 15 hospitals revealed that high effort-reward imbalance and overcommitment are significant predictors of burnout among Vietnamese healthcare professionals (Bui *et al.*, 2022). Furthermore, Vietnam's aging population is projected to increase demand for chronic disease management, posing additional pressure to an already stretched system (Glinskaya *et al.*, 2021). These contextual factors, including insufficient human resources, skill disparities, inconsistent infrastructure, and population aging, highlight the urgent need for technological interventions to support the healthcare workforce and improve service delivery.

AI technologies offer significant potential to alleviate the burdens faced by Vietnam's healthcare system. For example, remote patient monitoring and predictive analytics can reduce in-person visits and ease patient load by enabling chronic disease management outside traditional settings (Nadarzynski *et al.*, 2019; Thu, Nguyen and Taylor-Robinson, 2023; Kurniawan *et al.*, 2024). AI-powered chatbots and virtual assistants can support triage, appointment-scheduling, and care coordination, helping to address staff shortages in primary care and urban hospital clinics (Thu, Nguyen and Taylor-Robinson, 2023). Additionally, AI-based decision support tools (AIMDSS) integrated into radiology and clinical workflows, such as VinDr-CXR, have demonstrated improvements in diagnostic accuracy and throughput, potentially reducing diagnostic backlogs (Thu, Nguyen and Taylor-Robinson, 2023). By augmenting clinical capabilities and automating routine tasks, AI can help bridge human resource gaps, reduce provider fatigue, and improve access to care, especially in underserved areas.

AI adoption in Vietnam is still at an early stage, but momentum is growing. Vietnam's overall AI adoption rate across industries stands at a modest 9%, markedly lower than the global average of approximately 23%, healthcare applications are seeing noteworthy adoption efforts (Thu, Nguyen and Taylor-Robinson, 2023). This includes AI-based platforms such as DrAid, used in several tertiary institutions for X-ray, mammogram, and CT scan analysis to detect lung, breast, testicular, and prostate cancers (Thu, Nguyen and Taylor-Robinson, 2023). Furthermore, private-public initiatives, supported by major tech companies and government agencies, have begun to scale up AI infrastructure and talent (e.g., Nvidia's national AI research centre collaboration) (Vu and Fenton, 2024). While still emerging, such developments indicate a clear upward trajectory for AI integration in healthcare. Meanwhile, a current state of medical AI adoption in Vietnam is mostly refer as nascent. A 2025 assessment of five major public hospitals found that while Hospital Information Systems (HIS), Laboratory Information Systems (LIS), and PACS are widely implemented, advanced digital health technologies such as AIMDSS remain nascent (Tran *et al.*, 2023).

Given the nascent stage of medical AI adoption in Vietnam, there is currently no official or comprehensive data on adoption rates or the overall state of implementation. Existing information is fragmented and largely drawn from a limited number of independent reports and media sources that provide only partial insights into the adoption of medical AI in the country. Specifically, medical AI adoption in Vietnam has been most visible in large tertiary public hospitals and advanced private healthcare providers, where AI systems are primarily deployed as clinical decision support tools rather than autonomous decision-makers. A representative example is VinBrain's DrAid², an AI-powered medical imaging platform implemented in major public hospitals such as Central Military Hospital 108, Hue Central Hospital, National Lung Hospital, Hai Phong Lung Hospital, Ho Chi Minh Medical University Hospital, as well as private hospital networks including Vinmec International Hospital (VTV Online, 2024). DrAid supports radiologists in interpreting chest X-rays and CT scans by detecting abnormalities such as lung nodules and pneumonia, with AI outputs reviewed and validated by physicians within routine clinical workflows. Alongside domestic solutions, internationally developed systems have also been introduced. For instance, IBM Watson Oncology has been piloted in selected oncology centers, including the National Cancer Hospital, Phu Tho General Hospital, and HCMC Oncology Hospital,

² The illustration of the DrAid of VinBrain is in the Appendix 3, page 183

to assist oncologists by providing evidence-based treatment recommendations derived from medical literature and clinical guidelines (KPMG and Oxford University Clinical Research Unit, 2020)³. Overall, these cases indicate that AI adoption in Vietnam's healthcare system is characterized by incremental integration, physician oversight, and growing but still limited patient exposure, providing a realistic context in which consumers form beliefs, reasons for, and reasons against adopting AI-supported healthcare services.

Despite the substantial potential of artificial intelligence (AI) to transform Vietnam's healthcare system, particularly in mitigating workforce shortages, improving diagnostic accuracy, and enhancing care delivery, the integration of advanced AI applications, such as Artificial Intelligence Medical Decision Support Systems (AIMDSS) remains limited (Thu, Nguyen and Taylor-Robinson, 2023; Tran *et al.*, 2023). While early adoption efforts have shown promise, some study suggests that infrastructural, regulatory, and sociocultural barriers constrain widespread implementation (Vuong *et al.*, 2019). Regarding the regulation of medical AI adoption, AI-pioneering countries have adopted diverse approaches to medical AI regulation (Palaniappan, Lin and Vogel, 2024). Countries (e.g. USA, UK, and Singapore) mostly adopt a soft-law approach toward the use of AI in healthcare, including professional guidelines, voluntary standards, and codes of conduct that are adopted by governments and the industries. On the other hand, some countries have adopted legal frameworks to regulate the use of AI in healthcare practice, such as the European Union and China (Palaniappan, Lin and Vogel, 2024). Regarding developing countries, regulatory approaches to AI in healthcare are mostly still in the early stages, often relying on soft-law measures or broad national strategies rather than fully developed binding laws. For example, a comprehensive, standardized guideline and legal framework for AI in healthcare in Vietnam remain lacking, posing a challenge for adoption by medical facilities, physicians, and patients. Given the ambiguity surrounding the implementation of medical AI, the complexity of healthcare decision-making and the high stakes involved, patients have expressed concerns and resistance toward medical AI adoption (Plsek and Greenhalgh, 2001; Li and Wang, 2024; Khanijahani *et al.*, 2022; Yang, Ngai and Wang, 2024). Thus, understanding the factors that facilitate or hinder consumer adoption of such systems is critical in a developing-country context like Vietnam.

³ The illustration of the IBM Watson Oncology is in the Appendix 3, page 182

2.2. Research methodology

Given that medical AI is relatively new and its adoption is still nascent, it is important to understand the current state of its adoption in Vietnam. Such an understanding provides an overall picture of the types of medical AI currently in use, their adoption status, how they are being adopted in the healthcare system, and the general levels of awareness and practices surrounding medical AI among consumers in the Vietnamese context. Further, it is essential to explore the role of specific beliefs and context-specific factors in shaping rationales for or against adopting medical AI, using the BRT, in Vietnam, where medical AI adoption is considered novel. The insights from this dissertation would help further specify hypotheses 6, 7, 9 and 10. Lastly, this dissertation aims to examine the impact of those beliefs, via the reasoning process, on consumers' intention to adopt medical AI.

To address these objectives, a sequential exploratory mixed-methods design was employed, incorporating both qualitative and quantitative phases. The research design is illustrated in Figure 1.5. The qualitative phase was conducted first to provide rich insights into the context of medical AI adoption in Vietnam and to refine the conceptual framework. This phase consisted of semi-structured interviews with key stakeholders (e.g., medical professionals, policymakers, AI technology experts, and consumers) and was followed by focus group discussions targeting young consumers. The qualitative approach enabled the researcher to explore consumers' perceptions, their beliefs, and belief-based antecedents of adoption, which are particularly important in a context where medical AI is novel and consumer understanding is limited (McCracken, 1988; Silverman, 2009).

Semi-structured interviews are well-suited to exploring the state of medical AI adoption in Vietnam from the perspectives of diverse stakeholders, including healthcare professionals, policymakers, and industry representatives. These groups are expected to offer diverse viewpoints and observations on how medical AI is being adopted. At the same time, incorporating a small number of consumers offers valuable insights into their perceptions and awareness of medical AI, as well as potential determinants of adoption. Their age differences may also yield contrasting views on medical AI adoption. Moreover, doctors' observations of patients' attitudes and perceptions further enrich the understanding of consumer perspectives at this stage.

On the other hand, focus groups enable researchers to observe group interaction, shared reasoning, and collective sense-making that are difficult to elicit in one-on-one settings (Morgan, 1996). The integration of these two methods enriches findings,

enhances validity, and enables the research to explore both personal reflections and interpersonal dynamics related to the adoption of medical AI (Patton, 2014). Furthermore, this focus group consists of young participants representing young consumers, who, according to KPMG (2020), are expected to become the fastest-adopting segment of medical AI. As KPMG (2020) suggests, nearly half of Vietnam's working-age population is under 34, creating favorable conditions for the adoption of innovative science and technology. This 'golden population structure' positions Vietnam well for the adoption of digital health solutions, such as medical AI. Focus groups then allowed the exploration of belief factors and reasoning of young consumers, key adopters of digital health technologies.

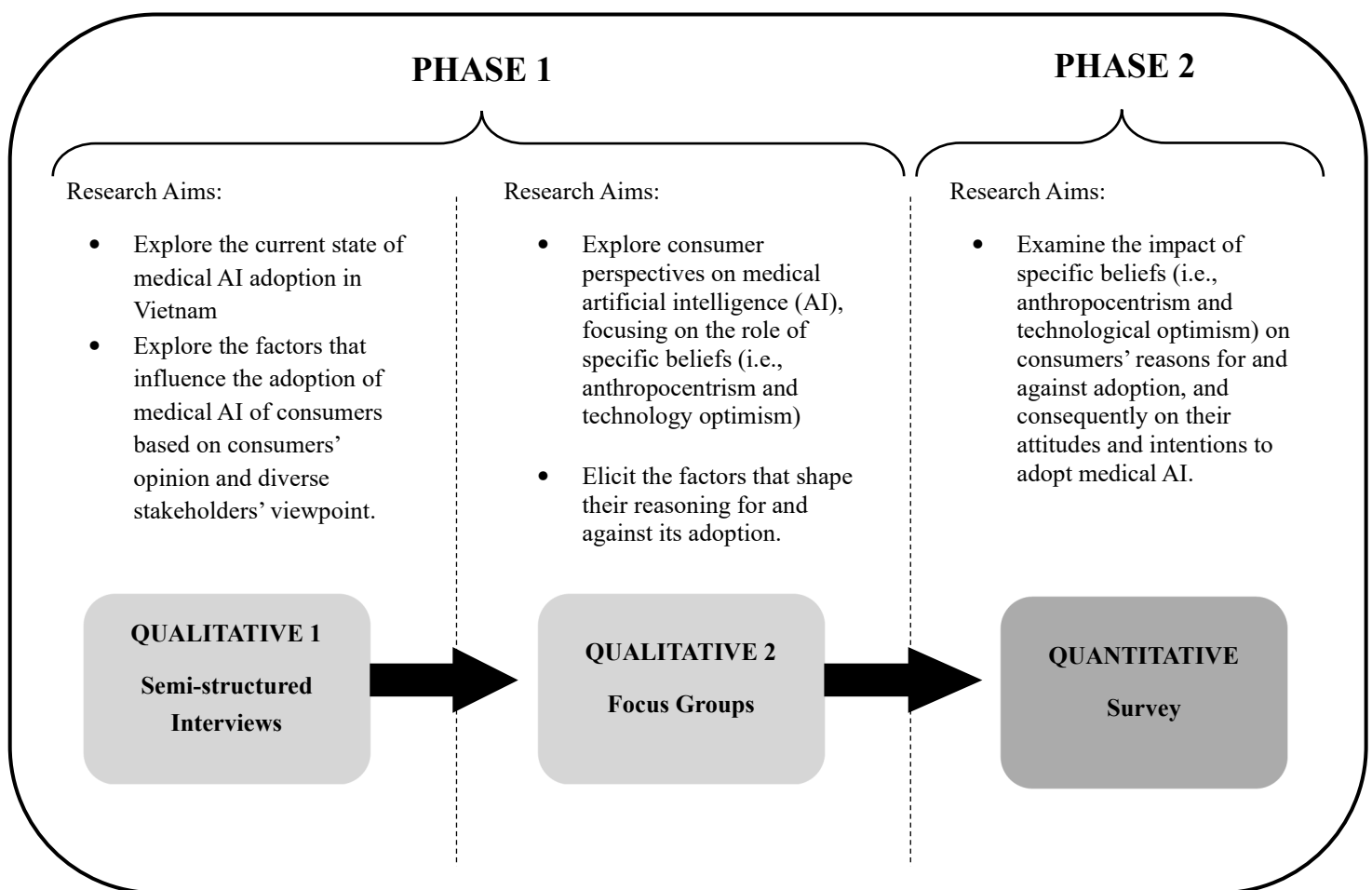


Figure 1.5. Research design of the dissertation

Additionally, conducting a preliminary qualitative study to elicit the context-specific reasons for and against adopting medical AI among consumers is consistent with the methodology proposed by Westaby (2005), which is commonly applied in BRT research (Westaby, 2005; Claudy, Garcia and O'Driscoll, 2015; Wagner and Westaby, 2020). In accordance with BRT, such elicitation studies enable the development of

categories representing both supportive and inhibiting reasons that are later incorporated into the main survey. In this dissertation, reasons were extracted by posing fundamental questions concerning beliefs, enabling conditions, and barriers that may hinder consumers' intention to adopt medical AI. Data were collected through semi-structured interviews and a follow-up focus group with young consumers. The semi-structured interviews, conducted with 17 diverse stakeholders (including consumers), offered a broad perspective on the determinants of medical AI adoption by capturing both consumer viewpoints and stakeholders' perspectives on factors that may contribute to consumer adoption. The focus groups allowed for a richer discussion, enabling participants to collectively reflect on their beliefs about the evolving role of medical AI and to elaborate on their rationales, which facilitate or hinder them from adopting medical AI in their healthcare services. Emerging themes from these qualitative phases were then identified and cross-validated with the literature to finalize the constructs related to adoption reasons. Within the BRT paradigm, *reasons for* and *reasons against* were subsequently operationalized as distinct second-order constructs to estimate consumers' adoption decisions of medical AI (Ashfaq *et al.*, 2021; Ahmad and Harun, 2023; Ahmad and Rasheed, 2024; Li and Wang, 2024).

Methodologically, combining multiple qualitative data collection strategies within the same phase is a recommended practice in exploratory research, especially in under-researched or emerging domains where both depth and breadth of understanding are necessary (Creswell and Plano Clark, 2018). Such a design aligns with the principle of methodological complementarity, where different qualitative techniques compensate for one another's limitations and strengthen the robustness of findings (Lambert and Loiselle, 2008).

In the second phase, the author conducted quantitative research to examine the proposed theoretical model. The quantitative phase involved a structured questionnaire to empirically examine the hypothesized relationships derived from the literature and qualitative insights. This mixed-methods strategy allows for the integration of exploratory depth and empirical validation, addressing both the "why" and "how" questions qualitatively and the "what" and "to what extent" questions quantitatively (Fetters, Curry and Creswell, 2013; Creswell and Plano Clark, 2018). This research design also responds to the call to use other methodologies to study AI adoption, including mixed-methods approaches (Jain, Wadhwani and Eastman, 2024).

2.2.1 Phase one: Qualitative study

This qualitative phase comprises two complementary methods: semi-structured interviews and focus group discussions. Each was designed to fulfill distinct but interrelated research objectives within the context of medical AI adoption in Vietnam.

2.2.1.1. Semi-structured interviews

Sample selection

The primary purpose of these semi-structured interviews is to explore medical AI adoption practices, particularly in Vietnam, an emerging Asian market, and the factors that influence adoption from the consumer perspective. To fulfill these objectives, the research employed a purposive sampling strategy (Patton, 2014), targeting individuals with relevant experience or involvement in the development, implementation, policy-making, or use of medical AI technologies. A total of 17 informants were recruited between 2023 and 2024 through the researchers' professional network, spanning across three key stakeholder groups: healthcare professionals, policymakers, and consumers.

Given the nascent yet rapidly evolving state of medical AI in Vietnam, the selection of informants was deliberately diversified to capture a holistic understanding of the adoption landscape. The sample includes senior and junior medical doctors from various specialties (e.g., gastroenterology, endoscopy, and medical imaging), many of whom have been directly involved in AI-related projects or clinical applications. Policymakers from the Ministry of Health were included to provide insights into the regulatory and strategic framework supporting AI integration in the national healthcare system. Furthermore, representatives from the healthcare industry and medical technology startups were selected to offer practical perspectives on technological readiness, implementation challenges, and commercial adoption. Lastly, a small group of digitally literate consumers across different age groups was interviewed to capture their perceptions and views on factors that could determine their intention to adopt medical AI.

This combination of expert, institutional, and consumer perspectives enabled the study to capture diverse opinions, thereby uncovering domain-specific factors influencing consumer adoption of AIMDSS. The diversity of informants' roles, organizational affiliations, and backgrounds also enhances the analytical validity of the study by encompassing both top-down (policy and system-level) and bottom-up (practice- and user-level) viewpoints. The information of informants is provided in Appendix 4.

Data collection and analysis

In this dissertation, the author recruited seventeen informants in the period 2023-2024 to gain a preliminary understanding of the state of medical AI adoption in Vietnam and the factors that could influence its adoption in the Vietnamese healthcare system. The interviews lasted 30 to 45 minutes and were conducted at the informant's office or at other locations chosen by the informants. All interviews were recorded and transcribed within 24 hours.

At the beginning of each interview, the researcher explained the study's objectives and engaged informants with introductory questions to foster a relaxed and open environment. To establish a shared understanding, benchmark examples were provided to clarify key terms, including "AI," "medical AI," and "medical AI adoption." The interview process consisted of two rounds. The first round gathered background information on informants' professional profiles, their exposure to technology, and their awareness of AI in healthcare. The second round explored their perceptions of medical AI adoption, perceived enabling and inhibiting factors, and views on whether AI could replace human physicians. Interviews continued until theoretical saturation was reached, defined as the point at which no new themes or insights emerged from the data (Guest, Bunce and Johnson, 2006).

The data were analyzed using the reflexive thematic analysis approach outlined by Braun and Clarke (2006). The analysis proceeded through six iterative phases. First, the author familiarized themselves with the data by repeatedly reading the transcripts, noting initial observations and potential patterns. In the second phase, the author generated initial codes by systematically identifying meaningful segments across the dataset. Coding was conducted inductively, ensuring that codes remained closely tied to participants' accounts rather than to preconceived theoretical categories. In the third phase, codes were examined and collated into candidate themes that captured broader patterns of meaning related to consumer reasoning about medical AI adoption. During phase four, these preliminary themes were reviewed and refined by assessing their coherence with coded extracts and the dataset as a whole. Themes that lacked sufficient evidential support were revised, merged, or discarded. Phase five involved defining and naming the themes through deeper analytic interpretation of their underlying meaning, scope, and boundaries. In the final phase, the themes were integrated into a coherent analytical narrative that explains how consumers make sense of medical AI and the factors that shape their adoption intentions. Throughout the entire analytic process, the

author adopted a reflexive stance, continually questioning assumptions and documenting interpretive decisions. Regular discussions with academic supervisors further enhanced the rigor and trustworthiness of the analysis.

2.2.1.2. Focus groups

Sample selection

To explore consumer perspectives on medical AI, including the role of specific beliefs and the factors shaping reasoning for and against its adoption, and specifying the hypotheses 6, 7, 9 and 10, nine focus group discussions were conducted with participants from a business school in Vietnam. A purposive sampling strategy was adopted to recruit participants who reflect a key demographic likely to engage with emerging healthcare technologies. The sample consisted of undergraduate and master's students, aged 19 to 27, currently enrolled in business and related programs. This age group was chosen based on the assumption that they tend to exhibit higher digital literacy, greater exposure to technological innovations, and a stronger inclination to adopt new technologies earlier than other demographics (Rogers, 2003).

Each round of data collection involved three focus groups, with 7 to 9 participants per group, consistent with methodological recommendations for generating diverse yet manageable discussions (Krueger and Casey, 2015). Participants were recruited through in-class announcements and institutional communication channels. Efforts were made to ensure diversity in gender and academic level across groups, while maintaining homogeneity in educational background to foster peer-based dialogue.

Data collection and analysis

Participants, including bachelor's and master's students, are in a similar age range (19-27 years old). They were recruited in three rounds with a total of 73 participants. In every round, the author created three groups, each consisting of seven to nine participants. The participants shared a similar education level (i.e., undergraduate, or master students) and the gender ratio was relatively balanced for each group. The authors assumed the moderator role. All focus group discussions were held after class on campus as part of their extracurricular activities. During the focus group discussions, participants were invited to share their views on key issues, including their awareness and experience with medical AI, perceptions of its role in healthcare, opinions on whether medical AI could replace or complement human tasks in healthcare, willingness to use such technologies and the factors influencing their decisions, as well as the distinctive characteristics of young consumers who may be particularly willing, or reluctant, to

adopt medical AI. To avoid misinterpretation of the term, a specific example was provided to stimulate discussion of the AIMDSS implemented in two large local private hospitals. To elicit factors influencing consumers' intention to adopt medical AI, the data was analyzed using reflexive thematic analysis, as outlined by Braun and Clarke (2006).

2.2.2. Phase two: Survey

2.2.2.1. Sample and data collection

In the second phase of this research, a structured survey was conducted to examine the determinants of consumers' intention to adopt medical AI in healthcare, using the proposed theoretical framework. Respondents were recruited through both online and offline channels. For the online distribution method, the questionnaire was disseminated to current undergraduate and graduate students, alumni of universities in Hanoi, and additional participants via online platforms such as Facebook and Zalo. For the offline method, data collection took place at two large hospitals in Hanoi, where visitors and patients were invited to participate voluntarily. The age of participants in the sample group is at least 18, mirroring the fundamental demographic characteristics of the actual survey population. These sampling strategies were chosen to reach a broad segment of Vietnamese consumers, particularly those with relatively higher levels of education and potential exposure to medical technologies, key considerations in studies on technology adoption in healthcare (Venkatesh et al., 2012).

Before participation, all respondents were informed about the study's objectives, confidentiality policies, and their right to withdraw at any time. After screening for completeness and validity, 487 responses were retained for analysis. The sample size of 487 respondents is well above the recommended thresholds for PLS-SEM. According to the "10-times rule," the minimum requirement is ten times the largest number of structural paths directed at a construct, which in this model is far below 487 (Barclay, Higgins and Thompson, 1995). Another recent simulation-based method confirms that PLS-SEM achieves reliable estimates with much smaller sample sizes than older heuristics (such as the 10-times rule) suggested by Kock and Hadaya (2018). According to Hair et al. (2022), the most appropriate way to determine sample size in PLS-SEM is through statistical power analysis. For a medium effect size ($f^2 = 0.15$), a 5% significance level, and a power of 80%, the minimum required sample size ranges from approximately 92 to 160 cases, depending on the number of predictors (Hair *et al.*, 2022). With 487 valid responses, the sample size in this dissertation comfortably exceeds these requirements, ensuring adequate statistical power.

2.2.2.2. *Measurements and questionnaire development*

A structured questionnaire was developed, comprising four integrated sections to address the research objectives comprehensively. Section 1 introduces the study and defines key concepts, including AI, medical AI, and their practical applications in healthcare. This section also incorporates illustrative examples to help respondents better understand how AI systems function in medical contexts. Furthermore, it outlines ethical considerations, including respondents' confidentiality and procedures for obtaining informed consent. Section 3 includes 69 items designed to capture a wide range of constructs relevant to the study. These items were adapted from validated scales in prior research and modified to align with the specific context, target population, and thematic focus of the investigation. Section 4 concludes the questionnaire with five demographic questions concerning age, gender, educational attainment, and income level. Construct measurements, along with the rationale for any adjustments, are described as follows.

Intention to adopt medical AI

Regarding adoption intention towards AIMDSS (i.e., medical AI), as with other TPB factors, Ajzen's (1991) measurement scale for purchase intention has been used in various research contexts, especially in studies of luxury product consumption. Therefore, in this dissertation, the author also adapted the scales from Ajzen (1991), each with three items: 'I intend to...', 'I plan to...', and 'I will try to...'. To enhance contextual relevance and predictive validity, an additional intention item, 'I intend to use AIMDSS in the next visit for medical examination services', was included. This adaptation aligns with the TACT principle (Target, Action, Context, Time), as recommended by Fishbein and Ajzen (2011), which posits that behavior prediction improves when intention measures are specific to the behavioral context. Related approaches, such as implementation intentions (Gollwitzer, 1999) and time-specific items in health behavior research (Maher *et al.*, 2017), further support the validity of this adaptation. Study of Chong (2013) has similarly tailored intention items to specific use scenarios to capture short-term, actionable intentions, particularly in domains where behavioral execution depends on situational triggers. The scale for intention to adopt medical AI is presented below:

Table 2.1. The scale of adoption intention toward AIMDSS

Variable	Items	Sources
Adoption intention toward AIMDSS (INT)	I intend to use AIMDSS when using medical examination services.	Adapted from Ajzen (1991)
	I will try to use AIMDSS when using medical examination services.	
	I intend to use AIMDSS in the next visit for medical examination services.	
	I plan to use AIMDSS when using medical examination services in the future.	

Attitude toward AIMDSS

In this dissertation, a shortened three-item attitude scale was adapted from Ajzen's (1991) guidelines to assess participants' evaluative orientation toward the use of AIMDSS. The decision to adopt a short-form version aligns with prior studies that have demonstrated the reliability and validity of abbreviated attitude measures in technology adoption (e.g. Taylor and Todd (1995)). The chosen wording substitutes "right choice" and "right decision" for Ajzen's originally suggested "wise" or "good," which are semantically equivalent yet more congruent with the clinical and evaluative nature of medical technology use. The scale items used in this dissertation are presented in Table 2.2.

Table 2.2. The scale of attitude toward using AIMDSS

Variable	Items	Source
Attitude (ATT)	For me to use AIMDSS is a right choice	Adapted from Ajzen (1991)
	For me to use AIMDSS is beneficial	
	For me to use AIMDSS is the right decision	

Techno-optimism

Techno-optimism refers to a favorable belief in technology's capacity to improve everyday life, productivity, and personalization. In this dissertation, the scale measuring this construct is adapted from the shortened five-item scale of Chung et al. (2015), who themselves drew on the original techno-optimism scale developed by Parasuraman (2000). This version is also adopted by other studies, for example, to study consumers'

acceptance of augmented reality technology (Álvarez-Marín, Velázquez-Iturbide and Castillo-Vergara, 2023). A modification was made to suit the healthcare context of this study better. Specifically, the author replaced the item “*Technology gives me more freedom and mobility*” with “*I like technologies that allow me to tailor things to fit my own needs*”, both of which originate from Parasuraman (2000)’s original pool of items.

This adjustment reflects the growing emphasis on personalized healthcare delivery, especially as AI technologies are increasingly used to customize medical information, treatments, and services to patients (He *et al.*, 2019; Topol, 2019). The revised item better captures the relevance of consumer-facing AI in healthcare, where user control and personalization are central to adoption motivation.

Moreover, the same modifications have been made in prior research to adapt the TRI scale to specific contexts. For example, Richey et al. (2007) have derived a similar shortened version of the technology optimism, but applied to firm-level examination. Thus, the adjustment preserves construct validity while enhancing contextual relevance for the adoption of medical AI among consumers in Vietnam.

Table 2.3. The scale of techno-optimism

Variable	Items	Source
Techno-optimism (TO)	New technologies contribute to a better quality of life	Adapted from Chung et al. (2015)
	I prefer to use the most advanced technology	
	Products/ services that use the newest technology are much more convenient for me to use	
	Technology makes me more productive in my personal life	
	I like technologies that allow me to tailor things to fit my own needs	

Anthropocentrism

Anthropocentrism in this dissertation is measured using a four-item scale developed by Fortuna et al. (2023) to capture the belief in human centrality and superiority within the natural order. These items reflect core anthropocentric beliefs in hierarchical human-nature relationships, exclusive epistemological authority, and moral precedence over non-human life. Fortuna et al. (2023) validated the scale across diverse populations, demonstrating strong internal consistency (Cronbach’s $\alpha > .85$) and sound convergent and discriminant validity using confirmatory factor analysis. Its robustness has been confirmed in his subsequent work (Fortuna *et al.*, 2024).

Table 2.4. The scale of anthropocentrism

Variable	Items	Source
Anthropocentrism (ANTH)	Man is the final link in the evolution of nature or, from the religious point of view, “the crown of creation.”	Fortuna et al. (2023)
	Man is a unique being, a special one in the Universe.	
	Only man can get to know the world objectively, as it is	
	The good of man is more important than the needs of any other creatures.	

Reasons for:

This research follows Westaby (2005) approach to model reasons for and against as formative higher-order construct. Westaby (2005, p. 105) notes that individuals often exhibit substantial variability in the importance they assign to different reasons when explaining behavior, suggesting that a single reason may account for a large proportion of the variance in attitudes or behavioral intentions. Building on this insight, Claudy et al. (2015) opted not to aggregate reasons into broad “reasons for” and “reasons against” indices. Instead, they modeled reasons as distinct second-order constructs, allowing the relative influence of specific reasons on consumers’ adoption decisions to be assessed more precisely Claudy et al. (2015, pp. 536–537). Claudy et al. (2015) further argue that this approach aligns with principles of measurement theory, which emphasize capturing the distinct contributions of underlying dimensions rather than masking them through aggregation.

The reflective–formative hierarchical component model (HCM) is suitable when the higher-order construct comprises conceptually distinct but causally contributing subdimensions, each measured reflectively (Becker, Klein and Wetzels, 2012; Sarstedt *et al.*, 2019). In such cases, a formative structure is appropriate because the subdimensions do not necessarily covary and should not be expected to reflect a single latent factor (Diamantopoulos, Riefler and Roth, 2008). In addition, this approach has also been adopted in other notable BRT studies (Ashfaq *et al.*, 2021; Ahmad and Harun, 2023; Li and Wang, 2024). Therefore, in this dissertation, the author models reasons for and against as formative higher-order construct. Given that reasons are context- and innovation-specific and thus needed to be elicited via an exploratory qualitative phase conducted in phase 1 before the surveys. Following the findings of phase 1, in this dissertation, *reasons for* adoption were composed of initial trust, personal

innovativeness in health technology, and modern self, each reflecting positively valenced justifications for using AIMDSS.

Initial trust

Initial trust in technology refers to a user's willingness to rely on a system in the absence of prior experience or extensive knowledge about its performance (Mcknight *et al.*, 2011). This study measures initial trust using a shortened four-item scale adapted from Oliveira et al. (2014), which initially assessed trust in technology in the context of mobile banking. The four items capture key facets of trustworthiness, including system reliability, perceived security, benevolence, and overall credibility. The adaptation maintains conceptual fidelity while tailoring item phrasing to the specific context of AI-driven medical decision support systems (AIMDSS). This abbreviated version was chosen for its parsimony and strong alignment with prior trust literature, enabling efficient measurement without sacrificing content validity.

Table 2.5. The scale of initial trust in AIMDSS adoption

Variable	Items	Source
Initial Trust (IT)	AIMDSS seem dependable	Adapted from Oliveira et al. (2014)
	AIMDSS seem secure	
	AIMDSS was created to help the patients	
	AIMDSS seem trustworthy	

Modern-self

The construct *modern self* reflects an individual's self-concept aligned with contemporary lifestyle values, emphasizing openness to change, hedonic consumption, and fashion consciousness. In this study, modern self is measured using five items adopted from Nguyen et al. (2009). These items capture key dimensions of modern identity, such as preference for fashionable appearance (“*I like people who dress in modern and fashionable ways*”), hedonic orientation (“*I think it’s important to enjoy a hedonic life*”), and openness to novelty (“*I like to try new products and services*”). Additionally, the items reflect modern lifestyle preferences (“*I like the modern lifestyle*”) and a positive attitude toward change (“*I think changes add excitement to one’s life*”). This scale has been validated and adopted in prior empirical studies across different contexts (Nguyen, Smith and Cao, 2009; Nguyen *et al.*, 2019). Together, these items effectively assess the extent to which individuals identify with a modern, progressive self-image, relevant to understanding their disposition toward adopting innovative products or technologies such as medical AI.

Table 2.6. The scale of modern self

Variable	Items	Source
Modern self (MS)	I like people who dress in modern and fashionable ways	Nguyen et al. (2009)
	I think it's important to enjoy a hedonic life	
	I like the modern lifestyle	
	I like to try new products and services.	
	I think changes add excitement to one's life	

Personal innovativeness in the domain of health technology

In this study, *Personal Innovativeness in the Domain of Health Technology* (PIHT) is measured using a domain-specific adaptation of a well-established scale developed by Agarwal and Prasad (1998). The three items are rooted in the foundational work of Agarwal and Prasad (1998), who introduced the concept of *innovative users in the information technology domain*. By tailoring the wording to focus specifically on *health technologies*, this construct captures respondents' propensity to embrace innovations within a targeted context, rather than reflecting a general trait of novelty seeking. This domain specificity is essential, as individuals may exhibit high innovativeness in consumer electronics or lifestyle gadgets, but behave differently when facing emerging medical technologies (1998). The original innovativeness scale has proved its robustness across diverse contexts and has been repeatedly shown to predict early adoption behavior. Examples of the original scale application include its use in studying the virtual reality simulation adoption of students (Fagan, Kilmon and Pandey, 2012), and medical AI adoption by doctors (e.g., Fan et al., (2020)). Consequently, this adapted version is justified both theoretically and empirically as an appropriate measure of how personal innovativeness manifests in medical AI adoption.

Table 2.7. The scale of personal innovativeness in domain of health technology

Variable	Items	Source
Personal Innovativeness in domain of Health Technology (PIHT)	If I heard about a new health technology, I would look for ways to experiment with it.	Adapted from Agarwal and Prasad (1998)
	Among my peers, I am usually the first to try out new health technologies.	
	I like to experiment with new health technologies.	

Reasons against:

Similar to *reasons for*, *reasons against* adoption is a formative construct, comprised of traditional self and perceived threat. These factors capture the psychological and cultural rationales consumers may use to justify avoidance of medical AI technologies.

Traditional self

The construct *Traditional Self* is measured using a five-item scale developed by Nguyen et al. (2009), which captures individuals' self-concept aligned with cultural conservatism, cautious consumption, and adherence to established social norms. The items include statements such as "*I always try to lead a thrifty life*" and "*I feel it necessary to be cautious when buying and using new products,*" reflecting a preference for stability, frugality, and risk aversion. Other items, such as "*I prefer to use markedly traditional products and services*" and "*It is important to observe and preserve traditional values in our social relationships*", emphasize the role of social conformity and respect for cultural heritage. This construct is particularly relevant in contexts such as healthcare technology, where individuals may resist adopting innovations that deviate from conventional practices. By capturing these culturally rooted dispositions, the Traditional Self scale serves as a meaningful predictor of consumer resistance or hesitation toward emerging technologies, including AI-based medical decision support systems. The scales' robustness has been shown in prior empirical studies (Nguyen, Smith and Cao, 2009; Nguyen *et al.*, 2019). Its measurement is illustrated below.

Table 2.8. The scale of traditional self

Variable	Items	Source
Traditional self (TS)	I always try to lead a thrifty life	Nguyen et al. (2009)
	I feel it necessary to be cautious when buying and using new products	
	I prefer to use markedly traditional products and services	
	For me, it is important to respect others' opinions about myself	
	For me, it is important to observe and preserve traditional values in our social relationships	

Perceived threat

In this study, *perceived threat* is conceptualized through two related yet distinct constructs, which are identity threat and realistic threat, conceptualised by Złotowski et al. (2017). In his work, identity threat reflects concerns that rapid AI advances may erode human distinctiveness and existential value. It is assessed with items such as “*Recent advances in AI are challenging the very essence of what it means to be human*” and “*Technological advancements in the area of AI are threatening human uniqueness.*” In contrast, realistic threat captures concrete, material fears associated with AI, as measured by items such as “*The increased use of AI in everyday life is causing more job loss for humans*” and “*In the long run, AI poses a direct threat to human safety and well-being.*” Subsequent research in the consumers’ AI adoption context, such as social robot service (Huang *et al.*, 2021), and resistance to AI (Mou, Gong and Ding, 2024). It has shown significant predictive relationships with consumers’ negative attitudes and consumers’ resistance. These empirical validations underscore the robustness and applicability of the identity and realistic threat dimensions, justifying their use in the present study of medical AI adoption.

Table 2.9. The scale of perceived threat

Variable	Items	Source
Identity threat (ITH)	Recent advances in AI are challenging the very essence of what it means to be human.	Złotowski et al. (2017)
	Technological advancements in AI are threatening human uniqueness.	
Realistic threat (RTH)	The increased use of AI in our everyday lives is causing more job loss for humans.	Złotowski et al. (2017)
	In the long run, AI poses a direct threat to human safety and well-being.	

In addition, other control variables, including perceived behavioral control and subjective norm, were incorporated into the model, as they represent important global motives that influence intention (Westaby, 2005; Sahu, Padhy and Dhir, 2020). In addition, other demographic factors are also considered, namely age, gender, personal income, family income. Scales of perceived behavioral control and subjective norms used in this study are provided below.

Table 2.10. The scale of control variables

Variable	Items	Source
Subjective Norms (SN)	My family thinks that I should use AIMDSS when using medical examination services.	Adapted from Ajzen (1991)
	Most of my friends and colleagues use AIMDSS when using medical examination services.	
	It is expected of me that I will use AIMDSS when using medical examination services.	
	The people who are important to me would support the adoption of AIMDSS when seeking medical care.	
Perceived Behavioral Control (PBC)	For me to use AIMDSS when using medical examination services would be possible.	Adapted from Ajzen (1991)
	When using medical examination services, if desired, I can use AIMDSS.	
	It is primarily up to me if I want to use AIMDSS when using medical examination services without difficulties (I can afford it)	
	It is not easy for me to access AIMDSS when seeking care at healthcare facilities. (R)	
Note: R indicates a reversed item.		

All measurement items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A brief and accessible definition of AI-based Medical Diagnostic Support Systems (AIMDSS) was provided at the beginning of the questionnaire to ensure participants' consistent understanding. The original English items were translated into Vietnamese following a rigorous back-translation procedure. The final questionnaire was pilot-tested on a small sample of young consumers to assess clarity and comprehension, and minor revisions were made based on their feedback. Demographic variables such as gender, occupation, and monthly income were included at the end of the questionnaire.

2.2.2.3. Data analysis

The analytical approach selected for this study was Partial Least Squares Structural Equation Modeling (PLS-SEM). Partial least squares structural equation

modeling (PLS-SEM) was employed in this study because it is particularly well suited for research that emphasizes prediction and explanation of variance in key outcome variables, such as consumers' intention to adopt medical AI (Hair, Ringle and Sarstedt, 2011; Wong, 2013). Moreover, this study applies BRT to examine a relatively underexplored cognitive mechanism linking beliefs to context-specific reasons and, subsequently, to attitudes and behavioral intention. Given the limited prior empirical research that models these belief–reason–intention pathways simultaneously, PLS-SEM is especially appropriate due to its suitability for exploratory theory development, its strong predictive orientation, and its capacity to handle complex models incorporating both formative and reflective constructs (Hair *et al.*, 2017). Beyond these advantages, the choice of PLS-SEM is further justified by the complexity of the conceptual model, which incorporates a reflective–formative higher-order specification. Specifically, the constructs “reasons for adoption” and “reasons against adoption” are modeled as formative higher-order constructs, each constituted by multiple reflective first-order constructs derived from focus group findings. Such hierarchical component models are best addressed using PLS-SEM, which provides well-established procedures for estimating reflective–formative relationships (Becker, Klein and Wetzels, 2012; Hair *et al.*, 2022). Therefore, in this study, sample characteristics and descriptive statistics were analyzed using SPSS 27, whereas the structural equation modeling (SEM) analysis was conducted using SmartPLS 4.

According to BRT and the specific objectives of this study, the author conceptualized reasons for and reasons against adoption as distinct higher-order constructs, each comprising theoretically relevant first-order dimensions. Accordingly, a two-stage approach was adopted for model estimation (Hair *et al.*, 2021). In the first stage, the measurement models of all lower-order reflective constructs were assessed for reliability and validity, including internal consistency (Cronbach's alpha and composite reliability), indicator reliability (outer loadings), convergent validity (average variance extracted, AVE), and discriminant validity using the heterotrait–monotrait (HTMT) ratio of correlations (Henseler, Ringle and Sarstedt, 2015). The second stage involved constructing the higher-order formative components using the latent variable scores of the validated lower-order constructs. Before second-level order estimation, collinearity among indicators for formative constructs was assessed using the Variance Inflation Factor (VIF), and the significance and relevance of formative weights were evaluated (Hair, 2014). After validating the measurement and structural models using the PLS algorithm, path coefficients are estimated using bootstrapping. Findings are reported in Section 3.2.

SUMMARY OF CHAPTER 2

Chapter 2 outlines the methodological framework for this dissertation, which explores the antecedents of consumer intention to adopt medical AI in healthcare in Vietnam. The chapter begins by introducing the research context and explaining the rationale for adopting a sequential exploratory mixed-methods design that integrates qualitative and quantitative approaches to generate deeper, contextually grounded insights.

The qualitative phase was conducted in two stages: semi-structured interviews with key stakeholders (including doctors, policymakers, industry professionals, and consumers) and focus groups with young consumers. These methods were chosen to explore differing perspectives on medical AI adoption and to identify belief-based drivers and barriers in the Vietnamese healthcare landscape. The procedures for participant recruitment, interview design, and thematic analysis are described in detail, drawing from established qualitative methods to ensure analytical rigor and trustworthiness.

Following this, the chapter presents the quantitative phase, which aimed to empirically test the proposed research model developed from the qualitative findings. A structured survey was administered both online and offline to a diverse sample of 487 Vietnamese consumers. The chapter elaborates on the sampling strategy, questionnaire design, and sample adequacy based on the number of observed variables. Finally, the chapter details the statistical analysis techniques used to assess the measurement and structural models. This breakdown of the research methodology enables readers to clearly understand the procedures followed in the study and the basis for the findings.

CHAPTER 3: RESEARCH FINDINGS

3.1. Qualitative Findings

3.1.1. *A nascent and fragmented adoption landscape of medical AI in Vietnam*

The current application of AI in Vietnamese healthcare is described as nascent, fragmented, and primarily in the early stages. This finding emerges from the semi-structured interviews conducted with multiple stakeholders across the healthcare industry in Vietnam⁴. Informant A, a leading medicine expert, optimistically stated that AI is "applied quite widely and popularly" in healthcare, particularly through its integration into "new generation machines" that assist in diagnosis and treatment. He also clarified that it is "just beginning to apply AI at a relatively simple level" and is not yet "popular" outside "large hospitals" and "major centers" in Vietnam. Informant J offered a more cautious perspective, stating that AI has "very little actual practical application" and is mostly limited to "clinical trials" or "experiments to build an AI model," with its "current prevalence" remaining "very low". Similarly, informant D, an expert in medical imaging, describes the current stage of medical AI adoption as "nascent, and because there are no legal regulations, no official products, there is nothing official yet", noting that foreign products are primarily used in "demo" mode due to a "lack of payment mechanisms" and inadequate "information technology infrastructure" in hospitals. Informant B, a medical professor, suggested that the primary applications of medical AI in Vietnam are either through research and clinical trials conducted at public hospitals or for commercial purposes in some private hospitals. Nevertheless, she noted that 'the number of such advanced hospitals equipped with medical AI is not significant. In contrast, informant C, a doctor, believes AI is "quite widespread," even extending to "medical record management" to reduce administrative time, envisioning a "smart hospital" system by 2028 mandated by the Ministry of Health. Informant E emphasizes AI as "very necessary" and "almost indispensable" in modern times, especially for quantitative analysis in imaging, though acknowledging its "rudimentary" stage in general adoption.

Regarding AI adoption, private hospitals appear more proactive. Both informants G and J, currently senior doctors at private medical facilities, noted that private healthcare providers are "very quick to adapt" and "bring new technologies" like AI into use, driven by market demand. Informant H, currently a vice head at an endoscopy

⁴ Information about the informants is provided in the informants overview table in the appendix 4

center of a public hospital in Hanoi, points out that "private hospitals or private clinics", such as TA hospital and TC hospital, are already utilizing AI. Informant L, a senior government official, further elaborates that private sector entities "tend to access newer AI versions faster and earlier" due to their "financial capacity" and more "favorable investment mechanisms". Informant E confirms this, stating that "private hospitals, even large or well-known ones, will have to integrate AI" into their new imaging equipment, mentioning VM hospital, TA hospital, and HN hospital as examples. Conversely, AI adoption in public hospitals faces distinct challenges. Informant D claims that, to date, "no single unit, public or private hospital, has actually purchased any AI software for practical use," with most applications being demos. However, developers prefer demos in "large public hospital systems" for data collection. Despite this, informants B and C suggest AI adoption might be "quite a bit more" prevalent in public hospitals due to a "top-down system" and Ministry of Health regulations. However, informant A highlights the "very large" financial challenges public hospitals face in adopting AI, and E finds its adoption still "rudimentary" in public settings, particularly at "grassroots levels". Informant J stresses that large public hospitals mostly use AI for "clinical trials" or "building an AI model," with very limited actual application, and points out the "huge disparity" in patient volume between public and private hospitals, which can hinder data collection for AI development in the private sector. He also notes that Vietnam's "technology infrastructure" is "not uniform," even in large public hospitals.

At the provincial level, both healthcare experts at central hospital level (e.g. informants B, E and H) and local senior doctors at provincial hospitals (e.g. F and G) agreed that the adoption of AI is considerably limited. Both informants B and E explicitly state that AI is "not yet truly present at grassroots levels" and that "smaller levels, such as provincial and district levels, still do not have it". Informants F and G offered similar observations regarding the adoption of medical AI in healthcare facilities at the provincial level. They pointed to "significant disparity" in infrastructure, information technology, and medical expertise between central, provincial, and district hospitals, which poses a significant barrier to widespread AI adoption. Informant C believes that comprehensive AI integration, including at the provincial level, must be initiated by "large hospitals" and "universities" that already possess the necessary infrastructure and robust data systems. Indeed, informant M, a Vice Head of a global technology giant with years of experience developing medical AI products in Vietnam, emphasized that central hospitals benefited from the 'established information technology infrastructure, government funding, and a huge influx of daily patients.' Furthermore, both entrepreneurs M and N observed that

central public hospitals benefit from their large pools of medical experts, who were 'superior in knowledge, skills, and also technology capacity and exposure.' In contrast, public hospitals at lower levels lacked access to the same resources, leading to 'disparities in expertise and infrastructure' that, in turn, further hindered the widespread adoption of AI. Thus, there is an apparent discrepancy in adoption between public and private hospitals, as well as between central and provincial hospitals.

3.1.2. Uneven awareness and exposure to medical AI of Vietnamese consumers

Both the semi-structured interviews and focus group discussions indicate that consumers in Vietnam have varied level of awareness and experience with medical AI. Further, their knowledge of medical AI was limited to hearsay or to information gained from watching TV and surfing the internet. The following excerpts illustrate this point.

From semi-structured interviews, consumers demonstrated varied level of awareness. For example, although informant Q is aware of AI in healthcare in general, he is not familiar with specific hospitals in Vietnam that use it. He further noted that he only trusted AI services from "reputable institutions or foreign professional systems". Informant P has "heard a lot about AI in healthcare," particularly in endoscopy and administrative tasks, but has no personal experience or acquaintances who have used AI-assisted medical services. Meanwhile, informant O recalls hearing about AI in healthcare "about 5-7 years ago," associating its data aggregation capabilities for diagnosis and treatment suggestions, though noting these were "in their lab" and "not yet in actual practical use". He highlights the importance of "communication" in educating the public, noting that while "younger people" quickly adopt new technologies, "older people" are "very hesitant" and "unwilling to learn new things". He has not personally used AI-assisted medical services, nor does he know anyone who has.

Also, the interview findings suggest that public understanding of medical AI is still limited due to limited exposure and generational difference. Informant P notes that patients often "primarily know about AI through certain media" but "cannot truly understand" the immense difficulties of applying AI in medicine, which, unlike other fields, "cannot be redone" if a mistake occurs. Informant O points out a generational divide in technology acceptance, where "younger people" quickly embrace new technologies, but "older people are very hesitant" and "unwilling to learn new things," underscoring the need for public "communication". He also highlights that, for now, AI in healthcare has been "in their lab" and "not yet in actual practical use," limiting public exposure and trust.

Similarly, focus group findings suggest that some consumers are aware of medical AI, its application, benefits, and the health facilities equipped with such system. Conversely, some consumers viewed medical AI as too new, which made them feel skeptical about the technology.

I have heard about the use of AI in healthcare abroad quite widely, but it is not yet the case in Vietnam, it is still relatively new here. As far as I know, only a few hospitals are applying for it. (Male, Group 2)

Young consumers, such as those of Gen Z, are currently leading the new trends, such as digitalization, in various fields, including healthcare. I think they are starting to realize the practical applications of medical AI. From a Tivi program, I've learned that Hospital TA is using AI. I think some young people have received it quite positively. (Female, Group 3)

Also, many of the focus group participants expressed their perceptions of benefits associated with using medical AI, such as high diagnostic accuracy and efficiency, and the ability to provide unbiased diagnostic results. A participant shared her opinion as follows.

I'd feel comfortable when AI participates in both administrative and treatment processes to reduce the possibility of wrong judgment/diagnosis. It is a very modern technology, and unlike human beings, it is unbiased in providing diagnostic results! (Female, Group 6)

Despite that, some participants expressed their concerns about medical AI, including “being skeptical about AI as a too new technology, created by humans”, “fearing possible errors since it’s too new”, and “lack of human empathy in dealing with patients”.

The downside of AI compared with human doctors is that AI lacks emotions, empathy, and understanding (Female, Group 7)

3.1.3. Coexistence of techno-optimistic belief and human-centered belief

Across all focus group discussions, two interwoven streams of belief consistently emerged, underpinning participants’ reasoning: one rooted in anthropocentrism, reflecting concerns about the loss of human-centered care, and the other grounded in techno-optimism, highlighting enthusiasm for AI’s potential to improve the quality and efficiency of healthcare delivery.

3.1.3.1. Pervasive techno-optimistic belief toward AI in healthcare

Across the interviews, there is strong consensus on a positive, open attitude towards new technology and AI in healthcare. Most informants express a strong openness and enthusiasm for technological advancements. Informant E stated, "I am very fond of technology" and believed that staying with old technologies or viewpoints will quickly lead to obsolescence, emphasizing a desire to update new technologies in medicine. Informant J also identifies himself as "a very open person in the application of information technology to support work, especially in the medical field," explicitly stating his fondness for technology. Similarly, informant D declared himself "a very open person to new technologies," going further to say he "likes it even more than just being open". Informant C noted that "everyone would probably like it because it helps a lot in their work," and she actively seeks information about new and prominent fields like AI. Junior doctor, informant I, expressed that he was 'very interested in new technologies' and believed that AI is 'very good' for the future, particularly in fields such as surgery, where it can perform micro-surgeries with high precision. He further noted that AI has 'very good' prospects because it can perform repetitive tasks with greater accuracy than humans.

This positive individual outlook is generally mirrored at an institutional level, particularly from a policy-making perspective. Informant L, representing a Department of Science, Technology and Education at Ministry of Health, states that the general view of state management agencies regarding the application of information technology in general and AI in particular is a "strong support" aimed at creating a "truly open and transparent legal environment". this is reinforced by high-level directives such as Resolution 57 from the Central Committee, Resolution 3 from the Government, and Ministry of Health (MOH) Decision 787, all geared towards promoting scientific-technological breakthroughs, innovation, and digital transformation. Another MOH official, informant K, echoed this, stating that the application of AI is an "inevitable trend that all places must implement" and it is "a trend that is almost unavoidable in the whirlpool of society".

Consumers O, P, and Q, all relatively young professionals, exhibit varied yet often optimistic perceptions of AI and its adoption in medical contexts. Informant O, a marketing professional, enjoys exploring new technologies, stating, "I am very much interested in exploring new technologies". He views AI as a limitless tool, asserting, "The capability of using artificial intelligence in life is infinite. There is nothing that does not need AI". Although he considers current AI to be "immature," noting that "AI has not yet developed to a mature level and remains at a foundational stage," he

nonetheless trusts medical AI because of its evidence-based approach and ability to aggregate large volumes of data. He further explained, *"In my opinion, yes [I trust medical services with AI]. Because the current examination and treatment results and decisions are evidence-based, and when evaluated based on evidence, AI, machinery, and equipment will provide a much better result because it aggregates a sufficiently large database"*. Informant P, working in foreign relations, is highly enthusiastic about AI, explicitly stating, *"Definitely, definitely. I am quite eager to see what new things the future holds"*. He viewed AI as a self-developing technology that will reduce human workload and significantly alter the labor market, as he anticipates AI's *"arrival will change the labor market a lot"*. For medical AI, informant P believes it can achieve high precision in image recognition and diagnosis, potentially surpassing human accuracy: *"I'm quite sure that AI can do well with image recognition and diagnostic technologies... And with the accuracy of machines, it is often more accurate than humans"*. Further, he is willing to use such services, asserting, *"Definitely, definitely I will use it"* particularly if offered by reputable institutions or foreign professional systems. On the other hand, Q is less inclined to proactively explore new technologies but is familiar with common AI tools such as ChatGPT. Despite her general skepticism, informant Q views medical AI, particularly in endoscopy, as a "breakthrough" that can significantly reduce missed diagnoses for fatigued doctors. While she initially lacked trust in medical AI, her current work in a research setting has increased her confidence. All three generally prefer a combination of doctor and AI for medical services, recognizing AI's role as a valuable support tool rather than a complete replacement for human expertise, especially in diagnosis.

Thus, the general perception toward medical AI adoption is positive. All participants seem to be optimistic about the technology and its potential for broader adoption in both administrative and clinical settings. However, this enthusiasm is occasionally tempered by a practical assessment of AI's current capabilities. While open to AI, some interviewees acknowledge its limitations and avoid being overly optimistic about its adoption at this stage.

In group discussion, a significant number of participants expressed strong confidence in AI's capabilities, consistently citing its technological superiority and functional benefits as the basis for their support of medical AI integration. Their statements exemplify a belief in the superiority of artificial intelligence over human capabilities in medicine, reflecting an aggressive techno-optimism. This belief manifests as confidence in AI's diagnostic accuracy, computational capacity, and surgical precision. For example, one participant noted, *"AI can provide excellent services... even*

better than long-practicing doctors,” which reflects a perception that technological advancement can not only match but also exceed traditional medical expertise. Another emphasized AI’s role in micro-surgery, highlighting its *“extremely high precision,”* while others pointed to the ability of sensors to *“provide more accurate alerts”* and contribute to better diagnoses. Participants also linked AI to efficiency and data processing power, as evidenced in the comment: *“AI can replace a large portion of human work... I feel completely confident in it.”* These views suggest that optimism about AI’s potential is closely tied to perceptions of functional advantage, trust in technological development, and the belief that AI progress can meaningfully enhance healthcare outcomes.

3.1.3.2. Expression of anthropocentric belief in the healthcare context

Several informants suggested that AI should serve as a tool or assistant rather than replacing human doctors. From a consumer perspective, informant Q believes AI "cannot completely replace humans," though it can replace "a part". Informant P shares this sentiment, stating AI "cannot replace humans entirely," though it can be a "useful tool". From the perspective of physicians, both informants A and B state that AI "cannot completely replace humans," particularly in areas such as "patient counseling" and "psychological support". Informant B emphatically states that AI "cannot replace the real doctor" and should only act as a "supportive role". From a policymaker's perspective, informant L consistently reiterates that AI is a "support tool" or "assistant" and that the "final decision must be the doctor's". Informants highlight specific human attributes that AI cannot replicate, thereby cementing the central role of the human doctor. Specifically, informant E points out that AI cannot handle "emotional aspects," "psychological support," or humane communication, particularly in sensitive situations such as delivering complex diagnoses. Informant F stresses that human doctors possess "sensibility," "experience," and the ability to handle "unconventional clinical situations" that AI may lack. From an industry view, informant M acknowledges that AI may struggle with "empathy and compassion". Also, informant L asserts that human doctors, with their "feelings, emotions, and intellect," are a "higher-level variant" that machines cannot replace, emphasizing the need for empathy in patient care. Both informants A and F raise ethical concerns, stating that AI should not make "independent decisions" because "if something goes wrong with humans, it cannot be undone," and ultimately, humans "must bear all legal responsibility". Informant B also highlights concerns about "patient acceptance" of AI, given the "trust-based relationship" between doctor and patient, and emphasizes that "no patient seeks medical care just to talk to a machine".

Many participants in the focus group also expressed the same concern. They suggested that AI should be used alongside human doctors to improve patient outcomes. In other words, AI is not trusted as an independent tool capable of replacing humans. It is only trustworthy as a tool to improve human performance. Compared to humans, AI was considered inferior at complex tasks but superior at assisting doctors. The participants consider AI to be very effective for repetitive tasks that humans can perform, but less efficient.

I think that AI is only a tool for the (human) doctor. The doctor must be the one who controls, owns, and employs AI in treatment". (Male, Group 6)

Another consistent theme that emerged across all focus group discussions is participants' deeply rooted belief in the centrality of human qualities in healthcare, reflecting anthropocentrism. This belief manifests in various ways, including concern about AI's inability to replicate human empathy, creativity, and contextual understanding; skepticism about AI's adaptability in unpredictable medical scenarios; and a persistent view that doctors must retain control over medical decisions. Participants frequently referenced the irreplaceable value of emotional intelligence, stating, for instance, that "AI does not have emotions like humans," and warning that AI's blunt communication might demotivate patients. Such views position AI not as an equal or superior agent in care, but as a tool subordinate to human judgment, emphasizing that "doctors should be the ones to direct and be the master of AI". At the same time, another added, *"AI is just a supporting tool. Humans are the ones making the decisions"*. This perspective also extended to epistemological concerns. Specifically, AI is viewed as inherently limited because it is created by humans and lacks the lived experience and improvisational capacity that physicians bring to complex or novel cases. One participant expressed this sentiment clearly: *"Even if AI is programmed, there are still unpredictable events in diagnosis and treatment; therefore, doctors are still needed to deal with emerging situations or cases beyond AI's handling"* (Female, Group 6). Collectively, these narratives underscore a clear anthropocentric stance, in which participants regard human attributes (e.g., empathy, intuition, ethical discretion) as essential and irreplaceable in medical practice, thereby shaping their reluctance toward fully autonomous medical AI systems. However, it is worth noting that participants who held it did not entirely reject the adoption of medical AI. Instead, many participants supported its use as long as it was framed as a supportive tool rather than a replacement. This highlights the importance of role framing in shaping acceptance. Whether this pattern extends more broadly across the population needs further investigation.

3.1.4. Adoption rationales

From the focus group analysis, several adoption rationales have emerged to justify participants' intention to adopt medical AI.

3.1.4.1. Modern self as a 'pro reason' toward medical AI

Focus group participants described consumers who are most willing to adopt medical AI as modern, tech-savvy, open-minded, and receptive to try new things. Some shared that since young consumers grew up in the digital era, many of them are more receptive to new technology, and they are more likely to trust medical AI's potential. However, their acceptance is mainly based on a sense of self, rather than on knowledge or experience (i.e., initial trust), as stated in the following.

Young people often more open to technological development and is therefore more likely to adopt AI. I think we need to accept a certain level of failure [associated with new medical AI] to get what we want. Nothing is perfect! (Female, Group 5)

Perhaps, I would accept AI for diagnosis in the beginning of some simple diseases... But the human body is unlike other things; there are many factors that vary depending on each person. However, this technology [medical AI] is very promising, so I think we should somehow support it for future development. Thus, I would be open to a diagnosis done by AI for some cases. (Male, Group 7)

They [who are tech-savvy and enjoy trying new things] trust in [medical] AI's power and potential [in treatment]. However, I think they are risk takers because even modern AI technology can be wrong and unreliable. (Male, Group 9)

3.1.4.2. Personal innovativeness in the domain of health technology as a 'pro reason' toward medical AI

While most participants seem to be well aware of AI, some demonstrate a strong understanding of its application in healthcare and willingness to use the technology despite limited exposure. Participants expressed varying levels of willingness to engage with medical AI tools, particularly in ways that reflect early adopter tendencies and enthusiasm for technological advancement in healthcare. One participant emphasized the accuracy and efficiency of AI over traditional methods, underscoring the superior functionality of AI-driven tools. Further, one participant regarded young people as those who are most likely to adopt due to their innovativeness and willingness to be leaders in experiencing new technological trends in healthcare. This framing of AI adoption as a status-enhancing behavior (e.g., being a "pioneer" or "leader") implies a motivational

dimension beyond utility, in which innovation is pursued for both instrumental and symbolic reasons. Another participant demonstrates a proactive, supportive attitude toward emerging health technologies, even while acknowledging the complexity of health and the limitations of AI. This reflects personal innovativeness, particularly in healthcare, as evidenced by their openness to experimentation and early-stage use. He expressed an understanding that the technology may not yet be perfect, but still perceives value in contributing to its development by adopting it in lower-risk contexts (e.g., early-stage or simple illnesses). Such reasoning reflects an innovator mindset, which is willing to engage with novel health solutions ahead of the majority and take calculated risks in adoption.

I will use AI for health monitoring, such as tracking heart rate, as it would be more accurate than the manual method (Male, Group 5)

I think some young people embrace this (referring to AI) very positively. I believe they would be willing to pay to use it, to become pioneers and leaders in this AI-integrated healthcare sector (Male, Group 6)

I would accept AI for diagnosing early-stage or basic illnesses, those that AI can identify based on experience or other influencing factors. AI could use those factors to make its diagnosis. In reality, the human body is unlike other things; there are many factors that affect health, and no two people are the same. Still, this technology has significant potential. I think it deserves some support in development, so I'm still open to accepting AI-based diagnoses for certain diseases. (Male, Group 7)

3.1.4.3. Initial trust as a 'pro reason' toward medical AI

Third, the group discussions also suggested that initial trust shapes attitudes and intentions to adopt medical AI. The following is an opinion expressed by one participant.

I trust that AI is developed to assist humans, including in healthcare. My opinion is that there are still some incurable diseases, and even doctors with many years of experience can't cure them, why don't we find hope in something new like AI? If there is a ray of hope in a 'no hope' situation, the confidence in using AI would be quite high. (Male, Group 5)

I choose to trust AI like everyone else. Its potential, combined with human capability, will create a certain level of assurance. (Female, Group 7)

AI already holds the knowledge and experience of doctors worldwide, so I completely trust it. I know AI always works at 100%, whereas doctors might not. (Male, Group 8)

From this analysis, initial trust, personal innovativeness in health technology, and orientations toward a traditional self emerged as key rationales participants articulated for their intention to adopt medical AI. Accordingly, *reasons for adoption* will be operationalised through these factors, with a further examination of their appropriateness presented in Section 3.2.

3.1.5. Resistance rationales

In the focus group discussions, some participants expressed hesitation toward adopting medical AI despite holding generally optimistic views of the technology. Analysis of the focus group data revealed several rationales for resistance that participants used to explain their reservations toward adopting AI-based medical decision support systems.

3.1.5.1. Traditional self as a ‘counter reason’ toward medical AI

When asked about the reasons for their hesitancy toward medical AI, several participants cited unfamiliarity with the technology, reluctance to change, and continued reliance on traditional services. These are reflected in the following excerpts.

Some people simply don’t trust computer- or AI-based “doctors” to perform examinations and issue prescriptions. They prefer human contacts and human doctors as what they have been long-time familiar with. (Male, Group 6)

I do not know anything about [medical] AI. It is too new. I do not feel comfortable being treated by AI, and I do not know whether it is skilled. How can I trust it? I would rather have a doctor. (Female, Group 8)

I think most people nowadays still prefer traditional hospital services. Thinking about doctors with years of experience who can always give us the best advice is ingrained in many people's minds... Because medical AI is closely related to people’s health and lives, it requires careful examination before use. Some people are afraid that their health condition and life can be negatively affected [by medical AI]. (Female, Group 4)

3.1.5.2. Identity threat as a ‘counter reason’ toward medical AI

Additionally, consumers’ perceptions of specific threats emerge as psychological barriers to the adoption of medical AI. Both statements go beyond a general claim that AI lacks empathy. They identified a threat that medical AI applications can undermine the patient’s sense of self, agency, and moral worth in care. Specifically, both quotes express consumers’ concern not only about

informational harshness but also about the erosion of a valued identity, as patients may still fight the illness and sustain hope. More broadly, respondents fear that AI will deliver information in an objective and overly direct manner, without buffering or tact, and in ways that fail to recognize patients' unique physical and mental conditions. Moreover, the comparison with humans illustrates certain discrimination toward AI, as it is seen as an outgroup lacking characteristics such as emotions, empathy, and understanding. Taken together, these views reflect apprehension about the diminishing relational and human-centered aspect of care when medical AI is introduced.

AI cannot calm and reassure patients. When a disease is complex to treat, doctors still encourage patients to fight the illness. But if AI tells you something like how likely you are to survive, that would be very difficult for the patient and would not help them maintain the spirit to overcome their fate. (Male, Group 1)

I still think human doctors play the key role in diagnosis and treatment. The downside of AI compared with human doctors is that AI lacks emotions, empathy, and understanding. A human would not disclose everything to a patient if the condition is severe, whereas an AI system would be straightforward, which can demotivate patients who are very ill and cannot be cured. (Female, Group 7)

AI is flawed and inhumane (Male, Group 4)

3.1.5.3. Realistic threat as a 'counter reason' toward medical AI

In addition to being wary of identity erosion and the diminishing human aspect of care, some participants expressed concern about realistic issues, such as patient safety and doctor job loss, as consequences of medical AI adoption. Specifically, they express concrete concerns that AI applications in healthcare could still lead to diagnostic errors, requiring human backup. Meanwhile, a participant expressed a cautious attitude toward AI applications in general, as they could replace humans in certain jobs. Together, this threat reinforces their resistance to the use of AI.

I do not believe AI can reach the level of accuracy I trust; AI still makes many errors, and humans handle mistakes better. (Female, Group 8)

I feel uncomfortable being diagnosed by AI because it can confuse one disease with another. (Female, Group 8)

I think we need a doctor's help because AI may still make many errors in differentiating among diseases. (Female, Group 5)

Are we fully aware of how medicine-related jobs would be taken by AI...

and

...are the jobs, or the career path that we are pursuing, will remain viable, or whether they could be replaced by AI (Female, Group 6)

Following these findings, identity threat, realistic threat and traditional self emerge as strong rationale against adopting medical AI for consumers. As in the research design section, these context-specific reasons were elicited using the process suggested in the BRT (Claudy, Garcia and O'Driscoll, 2015; Gupta and Arora, 2017; Choudhary *et al.*, 2025).

3.1.6. Hypotheses specification

The qualitative findings suggests that both anthropocentrism and techno-optimism function as double-edged beliefs that generate rationales both for and against the adoption of medical AI. Among anthropocentric participants, there was a strong preference for human primacy in complex medical decision-making, with one participant insisting that “I think a human doctor should conduct diagnosis.” This conviction led some to articulate reasons against adoption, particularly concerning AI’s inability to manage unexpected or novel conditions: “even if AI is programmed, in treatment there will still be unexpected cases... it still needs doctors to support those situations.” Others echoed concerns about empathy and interpersonal communication, arguing that “AI does not have emotions like humans, it lacks empathy, and this could demotivate patients if they are told directly that their condition is severe.” Nevertheless, the same anthropocentric belief also generated reasons for adoption when AI was framed as an assisting tool. For instance, participants acknowledged that “AI would better be a supportive tool... the combination of doctor-AI would be better,” while others emphasized AI’s capacity to reduce error and enhance precision: “in treatment, doctors can still make mistakes, so using AI will reduce the chance of error.” These narratives illustrate that anthropocentric consumers are not uniformly resistant; rather, they balance recognition of human superiority with pragmatic acceptance of AI as a tool to extend human capabilities.

Similarly, techno-optimistic participants consistently expressed confidence in AI's transformative potential, often portraying it as more advanced than human doctors. One participant asserted that “AI has the knowledge and experience of doctors worldwide, so I trust AI completely.” At the same time, another declared that “AI can replace most human work, with higher accuracy and speed.” These statements reflect

clear reasons for adoption grounded in optimism about technological progress and reliability. However, the same techno-optimistic stance also produced reasons against adoption, as some participants qualified their enthusiasm by restricting AI to specific roles. As one noted, “My acceptance level is only around 30–50%. AI should only scan data and measurements; the doctor must still diagnose and decide on the treatment plan.” Another reinforced this cautious optimism, stating: “AI is very promising... but if it alone manages my treatment plan, I cannot completely trust it.” These extracts suggest that even techno-optimists, while enthusiastic about AI’s capability, remain aware of the risks of over-reliance without human oversight.

Taken together, these findings confirm the proposition of BRT (Westaby, 2005) that core beliefs underlie the rationales both *for* and *against* a given behavior. Anthropocentrism, by foregrounding human superiority, generates both supportive and restrictive arguments regarding AI adoption. Likewise, techno-optimism, by highlighting the promise of technological advancement, yields strong pro-adoption rationales while simultaneously motivating cautionary reasoning. Following the analysis, this study further specifies hypotheses 6, 7, 9, and 10, as follows.

H6: Technology optimism will be positively related to *reasons for* adopting AIMDSS

H7: Technology optimism will be positively related to *reasons against* adopting AIMDSS

H9: Anthropocentrism will be positively related to *reasons for* adopting AIMDSS

H10: Anthropocentrism will be positively related to *reasons against* adopting AIMDSS

Summary of qualitative findings

The qualitative analysis of semi-structured interviews and focus group discussions reveals important insights into consumer perspectives on the adoption of medical artificial intelligence (AI) in Vietnam. Participants demonstrated varying degrees of awareness and exposure to AI in healthcare, with most acknowledging that the technology is still in its early stages of implementation in the country. While some respondents had heard of or engaged with AI-driven applications (e.g., remote diagnostics, wearable health monitors), they emphasized that such technologies remain limited in accessibility, public visibility, and integration into mainstream clinical care.

From the discussions, several emerging themes were identified, including the beliefs that emerged as salient influences on participants’ perceptions of medical AI, as well as the reasons for and against medical AI adoption. The analysis reveals that participants’ adoption intentions are grounded in two pivotal beliefs: anthropocentrism

and techno-optimism. The former positions human-centeredness as essential to care quality, resisting the impersonal nature of AI, while the latter frames AI as a progressive force capable of delivering superior clinical outcomes. Specifically, participants with anthropocentric views emphasized the irreplaceable role of human doctors in providing emotional support and personalized care, expressing concern that AI lacks empathy and could undermine the moral and relational core of the patient–doctor relationship. They often reference AI as a force that disrupts the experience of receiving humane, emotionally attuned care. In contrast, participants exhibiting techno-optimism framed AI as a valuable tool for improving diagnostic speed and accuracy, citing its large data-processing capacity and objectivity.

When participants were asked about enabling factors for medical AI adoption, several prominent themes emerged among those expressing favorable attitudes, including personal innovativeness in health technology, an initial sense of trust in AI systems, and the alignment of adoption with a modern self-identity. Participants expressed their willingness to experience AI, though acknowledged the complexity of health and the limitations of the technology. Additionally, participants described their peers who would be open to trying medical AI as “tech pioneers,” reinforcing the significance of personal innovativeness in the health domain as a potentially key driver of adoption intention. Further, some participants linked AI adoption to modernity and progressiveness. Meanwhile, the term ‘trust’ consistently appeared as an important factor in their consideration of AI adoption in healthcare. Conversely, reasons against adoption seem to reflect participants’ traditional self-concept, their perceived realistic threats, and identity threats. Concerns centered around the emotional and identity-related dimensions of care, such as AI’s inability to provide empathy, human touch, and moral discretion under challenging diagnoses. Participants feared that blunt AI-generated prognoses could harm patient morale and diminish the relational quality of care. Others raised doubts about AI’s diagnostic reliability, citing a lack of transparency and the potential for errors or misinterpretations, particularly in complex or ambiguous medical cases. Thus, the author proposed that the reasons for and against adoption be captured through the set of factors that surfaced from the qualitative analysis.

Overall, the qualitative findings provide rich exploratory insight into consumer reasoning and beliefs regarding medical AI, especially in the Vietnamese context where such technologies are still emerging. However, while the data illuminate the key dimensions influencing consumer attitudes, they do not capture the underlying mechanisms or quantify the extent to which these factors shape behavioral intentions.

Therefore, to more rigorously examine how these factors influence the intention to adopt AI in healthcare, a quantitative study is warranted. Such an approach can test the relative impact of each factor within a structured theoretical framework, such as the BRT, and validate the emergent themes in a broader population.

3.2. Quantitative findings

3.2.1. Sample characteristics

After data screening, 487 valid responses were retained for the final analysis, of which 32% were from offline respondents. Additionally, respondents were drawn from diverse geographical locations across Vietnam. Although a majority of participants were based in Hanoi, over 60%, the sample also includes individuals from numerous provinces in the North, Central, and Southern regions, reflecting a geographically dispersed respondent pool. ApproximateThe demographic characteristics of the sample are summarized in Table 3.1. Females constitute the majority, comprising 63.9% (n=311) of the sample, while males account for 36.1% (n=176). The respondents are predominantly young, with the largest group aged 20-29 (55.4%, n=270), followed by those 18-20 and those aged 30-39, each comprising 15.2% (n=74). Participants aged 40-49 represent 9.9% (n=48), while the smallest age group, those over 49, accounts for just 4.3% (n=21). Given that medical AI represents an emerging digital health technology, younger consumers constitute an important segment of early adopters. To certain extent, this sample reflect the age demographic of Vietnam (UNDP, 2025), as median age in Vietnam is 33.4 years as of 2025 (United Nations, 2024). Recent consumer and market reports portray Vietnamese young adults as digitally native, heavy users of online platforms and smartphones, and increasingly health-conscious, allocating growing expenditure to wellness, supplements, and healthy food choices (BritCham Vietnam, 2021; McKinsey, 2021). Academic and industry evidence further shows that this tech-savvy, health-oriented cohort is highly receptive to digital health solutions – such as m-health apps, teleconsultations and personal health tracking, and is a key driver of Vietnam’s rapidly expanding digital health market (Nguyen *et al.*, 2022; KPMG and Oxford University Clinical Research Unit, 2020; Tran *et al.*, 2018; Do *et al.*, 2018). Although respondents over 40 are underrepresented (14 percent), their sample size remains adequate for analysis.

Regarding educational attainment, the majority of respondents completed high school (58.5%, n=285), with undergraduates or equivalent qualifications representing 27.3% (n=133) and postgraduate degree holders making up 14.2% (n=69). Regarding

income, nearly half of the respondents earn less than 5 million VND per month (49.1%, n=239), with the second most common income bracket being 5-10 million VND (14.2%, n=69). Smaller proportions of the sample reported incomes between 10-15 million VND (13.6%, n=66), 15-20 million VND (9.4%, n=46), and above 25 million VND (9.7%, n=47), with the smallest group earning between 20-25 million VND (4.1%, n=29). This distribution suggests the sample is predominantly young, moderately educated, and generally earning lower- to middle-income levels, reflecting a representative cross-section of consumers likely to encounter and make decisions about medical AI technologies in Vietnam.

Table 3.1. Sample Characteristics

Variables	Types	Frequency	Percentage
Gender	Male	176	36.1%
	Female	311	63.9%
Age	Under 20	74	15.2%
	20-29	270	55.4%
	30-39	74	15.2%
	40-49	48	9.9%
	Over 49	21	4.3%
Level of education	High school	285	58.5%
	Undergraduate or Equivalent	133	27.3%
	Postgraduate degree	69	14.2%
Income	Under 5million	239	49.1%
	5-10 million	69	14.2%
	10-15 million	66	13.6%
	15-20 million	46	9.4%
	20-25 million	29	4.1%
	Above 25 million	47	9.7%

3.2.2. Measurement model assessment

Aforementioned in chapter 2, in analyzing higher-order constructs (HOCs) with a formative–reflective hierarchical component model (HCM) in SmartPLS, the two-stage approach is a widely recommended method (Becker, Klein and Wetzels, 2012; Sarstedt *et al.*, 2019). This approach is especially suitable when the HOC is formative and composed of reflective lower-order components (LOCs), as it allows for accurate estimation without inflating the measurement error.

Stage one is estimation of Lower-Order Constructs. In this stage, author assess the measurement model by analyzing the reflective first-order constructs (LOCs) independently. This involves assessing the outer loadings, indicator reliability, internal consistency reliability (e.g., Cronbach’s Alpha, Composite Reliability), and convergent validity (e.g., AVE) of each LOC. Once validated, the latent variable scores of these LOCs are extracted and used as manifest indicators in the second stage. Results of this stage is below.

3.2.2.1. Descriptive statistics and correlation analysis

Descriptive statistics

The item-level descriptive statistics are presented below, followed by those of the lower-order constructs.

Intention to adopt AIMDSS

Based on the descriptive statistics provided and following the guidelines recommended by Hair (2014), the measures of intention to adopt AI-enabled medical decision support systems (AIMDSS) exhibit generally acceptable distributional properties. All four items (INT1 to INT4) have means ranging from 3.45 to 3.87, indicating a moderately high level of intention to adopt AIMDSS among respondents. The standard deviations range from 0.916 to 1.021, suggesting an adequate level of variability in the data.

Importantly, the skewness values range from -0.807 to -0.253, and the kurtosis values range from -0.342 to 0.499, all of which lie within the acceptable thresholds of ± 1 recommended for normality assumptions in PLS-SEM Hair (2014). Overall, the skewness and kurtosis values of all items fall within acceptable thresholds, indicating no severe deviations from normality and suggesting that the data distribution is suitable for subsequent multivariate analyses.

Table 3.2. Item-level descriptive statistics for intention to adopt AIMDSS

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
INT1	487	1	5	3.76	.926	-0.629	0.111	.499	.221
INT2	487	1	5	3.85	.916	-0.714	0.111	.457	.221
INT3	487	1	5	3.45	1.021	-0.253	0.111	-.342	.221
INT4	487	1	5	3.87	.956	-0.807	0.111	.471	.221
Valid N (listwise)	487								

Attitude toward AIMDSS

Based on the descriptive statistics provided for the attitude toward AIMDSS construct, the three observed items (ATT1 to ATT3) demonstrate acceptable psychometric properties according to Hair (2014). The mean values for the three items range from 3.52 to 3.91, indicating a generally favorable attitude among respondents toward adopting AI-enabled medical decision support systems. This suggests that, on average, respondents agree or moderately agree with positive statements about AIMDSS. The standard deviations are relatively consistent, ranging from 0.893 to 0.934. This indicates a moderate level of response dispersion, suggesting that although most participants hold a positive attitude, there is still some variation across the sample. In terms of skewness and kurtosis, all values fall within the acceptable ± 1 threshold, indicating that no severe deviations from normality and suggesting that the data distribution is suitable for subsequent multivariate analyses.

Table 3.3. Item-level descriptive statistics for attitude toward AIMDSS

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ATT1	487	1	5	3.62	.931	-.417	.111	-.028	.221
ATT2	487	1	5	3.91	.893	-.698	.111	.447	.221
ATT3	487	1	5	3.52	.934	-.190	.111	-.196	.221
Valid N (listwise)	487								

Anthropocentrism

The mean values for the anthropocentrism items range from 3.39 to 3.99, indicating a moderate to high endorsement of anthropocentric beliefs among respondents. This suggests that, on average, participants tend to agree with statements that reflect a human-centered worldview in the context of AI-enabled healthcare. The highest mean is observed for ANTH1 (3.99), suggesting stronger agreement on that item, while ANTH4 has the lowest mean (3.39), indicating relatively lower endorsement. The standard deviations vary from 0.937 to 1.255, reflecting moderate to high variability in responses. Notably, ANTH4 shows the largest spread (SD = 1.255), suggesting greater divergence of opinion among respondents for that item. Regarding skewness, all four items exhibit negative skew (ranging from -0.831 to -0.430), indicating slightly left-skewed distributions. This implies that a substantial portion of participants selected higher values on the scale, again indicating general agreement with anthropocentric statements. Kurtosis values range from -0.741 to 0.508, all within the acceptable ± 1 range suggested by Hair (2014), meaning the distributions do not present any serious problems related to peakedness or flatness. Overall, the items display approximately normal distributions with acceptable skewness and kurtosis, and the sample shows a generally positive orientation toward anthropocentric beliefs.

Table 3.4. Item-level descriptive statistics for anthropocentrism

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ANTH1	487	1	5	3.99	.937	-.831	.111	.508	.221
ANTH2	487	1	5	3.85	1.089	-.840	.111	.164	.221
ANTH3	487	1.0	5.0	3.616	1.0841	-.505	.111	-.309	.221
ANTH4	487	1	5	3.39	1.255	-.430	.111	-.741	.221
Valid N (listwise)	487								

Techno-optimism

The mean scores for the techno-optimism items range from 3.97 to 4.37, suggesting that, on average, respondents strongly agreed with techno-optimistic statements. The highest mean was observed for TO1 (4.37), while TO5, though still relatively high (3.97), was the lowest among the five. The standard deviations, ranging from 0.800 to 0.887, show relatively low dispersion. This indicates a moderate level of agreement among respondents, with responses clustering closely around the mean for all items. All items exhibit negative skewness (ranging from -1.335 to -0.704), indicating a left-skewed distribution with a higher frequency of responses at the positive end of the scale. This is consistent with a generally favorable view of technology among the sample population. The kurtosis values range from 0.423 to 1.997, with TO1 and TO2 showing relatively high positive kurtosis (1.997 and 1.720, respectively), indicating a more peaked distribution and fewer extreme values, further confirming that most respondents strongly agreed with these techno-optimistic items. Overall, the items show acceptable levels of skewness and kurtosis, meeting Hair (2014)'s threshold for normal distribution ($|\text{skewness}| < 2$ and $|\text{kurtosis}| < 7$).

Table 3.5. Item-level descriptive statistics for techno-optimism

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TO1	487	1	5	4.37	.800	-1.335	.111	1.997	.221
TO2	487	1	5	4.32	.823	-1.244	.111	1.720	.221
TO3	487	1	5	4.16	.881	-.913	.111	.582	.221
TO4	487	1	5	4.10	.887	-.909	.111	.727	.221
TO5	487	1	5	3.97	.881	-.704	.111	.423	.221
Valid N (listwise)	487								

Initial trust

The mean scores for the items range from 3.32 to 4.02, suggesting generally favorable trust toward AIMDSS, with variation across items. IT1 has the highest mean

(4.02), indicating stronger agreement on this item. In contrast, IT2 (mean = 3.32) and IT4 (mean = 3.38) show slightly lower levels of agreement. The standard deviations fall between 0.871 and 0.937, showing moderate variation in responses, with no evidence of extreme dispersion. The skewness values range from -1.019 (IT1) to -0.171 (IT4), indicating that all items are left-skewed, particularly IT1. This suggests that more respondents selected higher-scale values, indicating relatively high levels of trust, especially for IT1. Kurtosis values are all within the normal range (Hair, 2014) with IT1 showing a more peaked distribution (1.546), meaning responses were more concentrated around the mean for that item. The other items (IT2–IT4) have values near zero, indicating a fairly normal distribution without heavy tails or peaks. Overall, the descriptive statistics reveal those participants generally express moderate to high initial trust in AIMDSS, with some variability across items. The distributions are within acceptable thresholds of skewness ($< |2|$) and kurtosis ($< |7|$), indicating that the items meet normality assumptions for further analysis.

Table 3.6. Item-level descriptive statistics for initial trust

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
IT1	487	1.0	5.0	4.02	.871	-1.019	.111	1.546	.221
IT2	487	1.0	5.0	3.32	.937	-.261	.111	.044	.221
IT3	487	1.0	5.0	3.52	.881	-.289	.111	.144	.221
IT4	487	1.0	5.0	3.38	.915	-.171	.111	.121	.221
Valid N (listwise)	487								

Personal innovativeness in the domain of health technology

The mean scores for the items range from 2.90 to 3.66, suggesting moderate levels of personal innovativeness among participants. PIHT3 and PIHT1 show higher means (3.66 and 3.62, respectively), indicating moderate agreement with statements reflecting an openness or willingness to try health technologies. PIHT2 shows a lower mean (2.90), suggesting a relatively more conservative or hesitant attitude of participants toward being the pioneer in experiencing new health technology. This

seems reasonable, as individuals may become more cautious toward new health technologies when their personal health is at stake. Standard deviations range from 0.969 to 1.154, with PIHT2 showing the highest variability. This indicates broader variation in how participants perceive their willingness to adopt or experiment with health technology. Kurtosis values are also within the acceptable range (± 7), ranging from -0.714 (PIHT2) to 0.023 (PIHT3). These values suggest no significant issues with the distribution shapes (neither overly peaked nor flat). Overall, the distribution of responses meets the normality assumptions, supporting the use of this construct in further multivariate analyses.

Table 3.7. Item-level descriptive statistics for personal innovativeness in the domain of health technology

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PIHT 1	487	1	5	3.62	.969	-.293	.111	-.364	.221
PIHT2	487	1	5	2.90	1.154	.149	.111	-.714	.221
PIHT3	487	1	5	3.66	.996	-.540	.111	.023	.221
Valid N (listwise)	487								

Modern self

The descriptive statistics for the Modern Self construct indicate generally favorable attitudes toward modernity among respondents. The mean values for all five items range from 3.69 to 4.15 on a five-point Likert scale, suggesting that participants tend to agree with statements reflecting a modern self-concept. Notably, MS5 (“I see myself as modern”) has the highest mean (4.15) and the lowest standard deviation (0.831), indicating strong consensus. The distribution of responses is slightly negatively skewed (e.g., skewness of -0.953 for MS5), meaning that more respondents selected higher ratings. Kurtosis values are mostly near zero or slightly positive, indicating distributions that are fairly normal or slightly peaked. These statistics suggest that respondents generally identify with modern self, and the responses are both consistent and centered around agreement.

Table 3.8. Item-level descriptive statistics for modern self

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
MS1	487	1	5	3.69	.914	-.337	.111	-.085	.221
MS2	487	1	5	4.09	.899	-.922	.111	.849	.221
MS3	487	1	5	3.89	.913	-.597	.111	.141	.221
MS4	487	1	5	3.90	.914	-.676	.111	.340	.221
MS5	487	1	5	4.15	.831	-.953	.111	1.243	.221
Valid N (listwise)	487								

Traditional self

The Traditional Self construct displays a more varied pattern. Mean scores range from 3.26 (TS3) to 4.01 (TS2), reflecting a moderate level of endorsement for traditional self-identities. TS3 appears to be the least endorsed item, possibly indicating some tension or ambivalence toward certain traditional values. In contrast, TS2, with a mean of 4.01 and skewness of -0.844, suggests strong agreement with that specific aspect of traditional identity. The standard deviations are somewhat larger for certain items (e.g., TS4 at 1.120), implying more dispersed responses. Overall, the descriptive statistics indicate a complex perception of traditional values among respondents, with some items being more strongly endorsed than others.

Table 3.9. Item-level descriptive statistics for traditional self

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TS1	487	1	5	3.71	.963	-.438	.111	-.151	.221
TS2	487	1	5	4.01	.913	-.844	.111	.554	.221
TS3	487	1	5	3.26	.929	.098	.111	-.093	.221
TS4	487	1	5	3.52	1.120	-.416	.111	-.506	.221
TS5	487	1	5	3.81	.896	-.491	.111	.039	.221
Valid N (listwise)	487								

Perceived threat

The construct Perceived Threat is composed of two subdimensions: Realistic Threat (RTH) and Identity Threat (ITH). The descriptive statistics indicate moderate levels of perceived threat among respondents. For realistic threat, RTH1 has a mean of 3.73 with a standard deviation of 1.059, showing moderate agreement with some variation in responses. RTH2 has a lower mean (3.31) and a slightly higher standard deviation (1.112), indicating a broader spread of opinions. Skewness values for both items are negative, suggesting a slight tendency toward agreement. In the identity threat subdimension, ITH1 (mean = 3.72, SD = 0.989) shows a central tendency similar to RTH1, whereas ITH2 has a slightly lower mean of 3.46 and a higher standard deviation of 1.141. The negative skewness in both identity threat items also indicates that more respondents lean toward agreement, though the presence of mild kurtosis and standard deviations near or above 1 reflects some diversity in viewpoints. Overall, the data suggest that respondents perceive both realistic and identity-related threats associated with medical AI to a moderate extent, with a slight tendency toward agreement, though there is some variability in individual experiences or concerns.

Table 3.10. Item-level descriptive statistics for perceived threat

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
RTH1	487	1	5	3.73	1.059	-.503	.111	-.320	.221
RTH2	487	1	5	3.31	1.112	-.185	.111	-.554	.221
ITH1	487	1	5	3.72	0.989	-.606	.111	.079	.221
ITH2	487	1	5	3.46	1.141	-.356	.111	-.669	.221
Valid N (listwise)	487								

Table 3.11 presents the mean and standard deviation of the lower-order constructs. The descriptive statistics of these variables indicate that respondents reported moderate to moderately high levels across all constructs, with mean values ranging from 3.39 to 4.18 on the measurement scale. Among the variables, Technology Optimism exhibits the highest mean ($M = 4.18$, $SD = 0.73$), suggesting that respondents generally hold positive expectations toward the benefits of technology, including medical AI. Similarly, Modern Self ($M = 3.94$, $SD = 0.73$) and Intention to adopt medical AI ($M =$

3.73, SD = 0.84) also show relatively high mean scores, indicating a favorable self perception aligned with modernity and a generally positive adoption tendency.

In contrast, Personal Innovativeness in the domain of Health Technology records the lowest mean ($M = 3.39$, $SD = 0.87$), implying that while respondents are open to technology in general, they are more cautious when it comes to personally experimenting with or adopting new health technologies. The mean scores for Anthropocentrism, Attitude, Perceived Threat, Initial Trust, and Traditional Self cluster around the midpoint of the scale (approximately 3.55–3.71), reflecting a balanced coexistence of supportive and cautious orientations toward medical AI.

Regarding variability, the standard deviations range from 0.71 to 0.89, indicating acceptable dispersion and sufficient heterogeneity in respondents' perceptions and beliefs. Constructs such as Anthropocentrism ($SD = 0.89$) and Perceived Threat ($SD = 0.89$) exhibit relatively greater variability, suggesting greater divergence in respondents' views on human centrality and the potential risks of medical AI. Overall, the means and standard deviations indicate that the sample provides sufficient variation for subsequent analysis and reflects a generally positive yet nuanced stance toward medical AI adoption among Vietnamese consumers.

Correlation analysis

The correlation matrix shows that initial trust, attitude, and technology optimism are strongly associated with intention to adopt AIMDSS, suggesting that positive beliefs and trust play an important role in shaping adoption decisions. Identity threat and realistic threat correlate moderately with anthropocentrism and the traditional self, indicating that more traditional or human-centered beliefs are associated with higher perceived threats. Modern self and personal innovativeness in the domain of health technology are positively correlated with attitude, intention, and technology optimism, underscoring the role of self-concept and personal innovativeness in fostering more favorable views of medical AI.

Table 3.11. Descriptive statistics and correlation matrix

Variables	Mean	SD	1	2	3	4	5	6	7	9	10
1. Anthropocentrism	3.7136	0.8891	0.815								
2. Attitude	3.6817	0.8192	0.301**	0.891							
3. Perceived threat	3.5549	0.8855	0.387**	0.161**	0.823						
4. Initial trust	3.5616	0.7609	0.33**	0.749**	0.209**	0.845					
5. Intention	3.7341	0.8353	0.284**	0.747**	0.191**	0.682**	0.876				
6. Modern Self	3.9429	0.7280	0.531**	0.379**	0.310**	0.388**	0.469**	0.816			
7. Personal Innovativeness in the domain of Health Technology	3.3922	0.8737	0.375**	0.457**	0.276**	0.449**	0.522**	0.52**	0.843		
9. Technology Optimism	4.1823	0.7272	0.37**	0.545**	0.332**	0.524**	0.613**	0.646**	0.579**	0.853	
10. Traditional Self	3.6616	0.7080	0.484**	0.289**	0.461**	0.374**	0.358**	0.559**	0.373**	0.413**	0.736
<p>Notes: N=487. Two-sided test. ** p < 0.01.</p> <p>The diagonal shows the square root of the AVE.</p> <p>Values under the diagonal represents the inter-construct correlations.</p>											

3.2.2.2. Reliability and validity analysis

Outer loadings

The outer loadings for all items across constructs demonstrate satisfactory levels, indicating strong indicator reliability in the measurement model, as presented in Table 3.12. According to Hair (2014), outer loadings should ideally exceed 0.70 to confirm that indicators adequately represent their respective latent constructs. Most items meet or exceed this threshold. Notably high loadings are seen for constructs such as Attitude (ranging from 0.877 to 0.906), Intention to adopt (0.832 to 0.914), Techno-optimism (0.763 to 0.885), and Personal Innovativeness in Health Technology (PIHT1 = 0.889, PIHT3 = 0.888). These reflect strong convergent validity. Only a few items slightly approach but do not fall below the threshold (e.g., Traditional Self - TS4 = 0.655 and Anthropocentrism - ANTH4 = 0.726). Overall, the outer loadings provide robust evidence of construct validity and support the reliability of the measurement model used in this study. The outer loadings are reported in table 3.12.

Construct reliability and convergent validity

The reliability analysis results in Table 3.12 indicate that all constructs meet or exceed recommended thresholds for internal consistency and convergent validity, supporting the robustness of the measurement model.

Regarding internal consistency, Cronbach's alpha values for all constructs range from 0.769 (*Traditional self*) to 0.906 (*Techno-optimism*), exceeding the acceptable threshold of 0.70 (Hair et al., 2014). This indicates that the items within each construct exhibit good internal reliability. Although *Traditional self* has the lowest alpha (0.769), it still falls within an acceptable range.

Composite reliability (CR), which provides a more precise estimate of internal consistency than Cronbach's alpha, also supports these findings. All CR values are above 0.70, ranging from 0.771 (*Traditional self*) to 0.906 (*Techno-optimism*), further confirming satisfactory construct reliability.

Regarding convergent validity, the Average Variance Extracted (AVE) for all constructs also exceeds the minimum threshold of 0.50, with values ranging from 0.591 (*Traditional self*) to 0.795 (*Attitude*). This indicates that, on average, more than 50% of the variance in the indicators is explained by their corresponding constructs, providing strong evidence of convergent validity.

Table 3.12. Reliability and validity results

Variables	Items	Outer loadings	Cronbach's alpha	Composite Reliability	Average variance extracted (AVE)
Anthropocentrism	ANTH1	0.815	0.831	0.843	0.665
	ANTH2	0.873			
	ANTH3	0.84			
	ANTH4	0.726			
Attitude	ATT1	0.906	0.871	0.871	0.795
	ATT2	0.892			
	ATT3	0.877			
Intention	INT1	0.891	0.899	0.902	0.768
	INT2	0.914			
	INT3	0.832			
	INT4	0.865			
Modern self	MS1	0.741	0.873	0.879	0.665
	MS2	0.774			
	MS3	0.879			
	MS4	0.829			
	MS5	0.847			
Personal innovativeness in domain of health technology	PIHT1	0.889	0.796	0.828	0.710
	PIHT2	0.741			
	PIHT3	0.888			
Techno-optimism	TO1	0.881	0.906	0.906	0.728
	TO2	0.885			
	TO3	0.863			
	TO4	0.869			
	TO5	0.763			
Initial trust	IT1	0.767	0.865	0.868	0.713

Variables	Items	Outer loadings	Cronbach's alpha	Composite Reliability	Average variance extracted (AVE)
	IT2	0.864			
	IT3	0.86			
	IT4	0.884			
Traditional self	TS1	0.723	0.769	0.771	0.591
	TS2	0.756			
	TS3	0.744			
	TS4	0.655			
	TS5	0.796			
Perceived threat	ITH1	0.816	0.841	0.842	0.677
	ITH2	0.831			
	RTH1	0.798			
	RTH2	0.846			

Discriminant validity

The discriminant validity assessment, as shown in Table 3.13, was evaluated using the Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion, where values below 0.90 indicate satisfactory discriminant validity between constructs (Hair, 2014; Henseler, Ringle and Sarstedt, 2015). All HTMT values between pairs of constructs are below the conservative threshold of 0.90, suggesting that each construct in the measurement model is empirically distinct from the others. Thus, the results confirm that all constructs exhibit satisfactory discriminant validity based on HTMT analysis. This ensures that the observed relationships in the structural model are not confounded by multicollinearity or redundancy among constructs.

Table 3.13. Discriminant validity (HTMT)

	Anthropo- centrism	Attitude	Initial trust	Intention	Modern self	Personal innovative- ness in domain of health tech- nology	Perceived threat	Techno- optimism
Anthropo- centrism								
Attitude	0.343							
Initial trust	0.381	0.864						
Intention	0.313	0.843	0.776					
Modern self	0.615	0.433	0.447	0.523				
Personal innovative- ness in domain of health technology	0.464	0.542	0.532	0.6	0.6			
Perceived threat	0.463	0.189	0.248	0.222	0.368	0.337		
Techno- optimism	0.413	0.613	0.595	0.677	0.722	0.655	0.383	
Traditional self	0.59	0.345	0.451	0.419	0.662	0.432	0.558	0.483
<i>Discriminant validity – HTMT < 0.90 (for conceptually similar constructs)</i>								

Furthermore, the Fornell–Larcker criterion results provide strong evidence of discriminant validity in the model (Table 3.11). In all cases, the square root of the average variance extracted (AVE) on the diagonal is greater than the inter-construct correlations (Table 3.11) , thereby fulfilling the recommended criterion (Fornell and Larcker, 1981).

Overall, the measurement model was validated, confirming reliability, convergent validity, and discriminant validity. Accordingly, the latent variable scores of

the lower-order constructs (LOCs) were extracted and used as manifest indicators for the second-stage analysis.

3.2.2.3. Common method bias

Given that all data were collected from the same respondents using a single survey instrument, Common Method Bias (CMB) may pose a threat to the validity of the results. To evaluate this concern, both procedural and statistical remedies were considered.

From a procedural standpoint, anonymity was ensured, and the wording of the items was carefully refined to minimize ambiguity and social desirability bias, as recommended by Podsakoff et al. (2003).

From a statistical standpoint, the Variance Inflation Factor (VIF) values from the inner and outer models were examined as a proxy test for CMB. According to Kock (2015), VIF values below 3.3 suggest that CMB is unlikely to be a significant issue. In this study, all inner and outer VIF values were well below this threshold, ranging from 1.0 to 2.734, indicating no critical multicollinearity or method bias.

Table 3.14 reports the outer VIF values. All outer VIF values fall well below the conservative threshold of 3.3, suggesting no multicollinearity issues among the first-order constructs forming the second-order constructs *Reasons for* and *Reasons against* (Kock, 2015). This indicates that each lower-order component contributes uniquely to the higher-order constructs, validating the formative specification.

Table 3.14. Outer VIF values

Lower-order constructs	VIFs
Initial Trust	1.307
Modern self	1.437
Personal innovativeness in the domain of health technology	1.53
Perceived Threat	1.257
Traditional self	1.257

The inner VIF values for predictors in the structural model range from 1.000 to 2.734, all of which are below the critical threshold of 3.3, and far below the conservative threshold of 5.0 (Kock, 2015). This indicates no serious collinearity among the exogenous constructs in predicting endogenous variables such as Attitude, Intention, *Reasons for*, and *Reasons against*. The inner VIF values are presented in table 3.15 below.

Table 3.15. Inner VIF values

	Attitude	Intention	Reasons against	Reasons for	Technology optimism
Anthropocentrism	1.496		1.164	1.164	1.000
Attitude		2.202			
Intention					
Reasons against	1.566	1.381			
Reasons for	2.331	2.734			
Technology optimism	2.018		1.164	1.164	

3.2.2.4. Structural model assessment

The R^2 values represent the explanatory power of the model for each endogenous construct. According to the guidelines by Hair et al. (2011), an R^2 value of 0.75 is considered substantial, 0.50 moderate, and 0.25 weak. As reported in table 3.16, the model demonstrates moderate to strong explanatory power for *intention to adopt AIMDSS* ($R^2 = 0.633$), *attitude* ($R^2 = 0.546$), and *reasons for adoption* ($R^2 = 0.550$), suggesting that the specified antecedents adequately explain these outcomes. Meanwhile, *reasons against adoption* exhibits a weaker R^2 of 0.332, which remains acceptable in exploratory research contexts. These results indicate that the proposed model captures meaningful variance in key psychological drivers and behavioral outcomes related to AI adoption in healthcare.

The predictive relevance of the model was examined using the blindfolding procedure (Stone, 1974; Geisser, 1975). In table 3.16, all Q^2 values were greater than zero, confirming the predictive capability of the endogenous constructs (Hair *et al.*, 2021). Specifically, Attitude ($Q^2 = 0.429$) and Intention ($Q^2 = 0.480$) demonstrated large predictive relevance, while Reasons for ($Q^2 = 0.368$) indicated medium-to-large predictive relevance. Reasons against ($Q^2 = 0.228$) also exceeded the recommended threshold of 0.15, reflecting medium predictive relevance. These results provide strong evidence that the model possesses substantial predictive validity across both higher-order and lower-order constructs.

Table 3.16. Results of R^2 and predictive relevance Q^2

	R^2	Q^2
Attitude	0.546	0.429
Intention	0.633	0.480
Reasons against	0.332	0.228
Reasons for	0.550	0.368

The f^2 values offer insight into the effect sizes of individual exogenous variables on each endogenous construct. The f^2 values are illustrated in the below table 3.17. Notably, *reasons for* \rightarrow *attitude* ($f^2 = 0.535$) and *attitude* \rightarrow *intention* ($f^2 = 0.255$) exhibits large and moderate effect sizes, respectively, supporting the central role of attitude formation in the adoption process. *Technology optimism* strongly predicts *reasons for* ($f^2 = 0.715$), highlighting the importance of positive beliefs about technological progress. Additionally, *anthropocentrism* shows small to moderate effects on both *reasons for* (0.125) and *reasons against* (0.217), suggesting its dual influence on consumers' cognitive evaluations. Some paths, such as *reasons against* \rightarrow *intention* (0.001) and *reasons against* \rightarrow *attitude* (0.020), show negligible to small effects, indicating limited direct influence.

Table 3.17. f^2 result

Variables	Attitude	Intention	Reasons against	Reasons for
Anthropocentrism	0.001		0.217	0.125
Attitude		0.255		
Intention				
Reasons against	0.020	0.001		
Reasons for	0.535	0.158		
Technology Optimism	0.007		0.104	0.715

The Standardized Root Mean Square Residual (SRMR) is a commonly used goodness-of-fit index in Partial Least Squares Structural Equation Modeling (PLS-SEM). It measures the average magnitude of the difference between the observed and expected correlations. The result on this model fit indice is presented in the table 3.18. According to Hu and Bentler (1999), as well as Henseler et al. (2016), an SRMR value below 0.08 generally indicates a good model fit. In this model, the SRMR is reported as 0.07, which is under the recommended threshold. This suggests that the model has an acceptable fit, and the residuals between the predicted and observed correlation matrices are sufficiently low. Therefore, the structural model can be considered adequately specified in terms of overall fit.

Table 3.18. Model fit index

	Estimated model
SRMR	0.07

3.2.3. Hypotheses testing

Assessment of second-order construct

The second-order path estimates reveal the relative contributions of the lower-order constructs to the formation of the higher-order constructs *reasons for* and *reasons against* adopting AIMDSS. As presented in table 3.19, among the antecedents of *reasons for* initial trust exhibits the strongest influence ($\beta = 0.654, p < 0.001$), indicating that trust in the reliability and benevolence of AIMDSS plays a critical role in shaping positive justifications for adoption. Modern self ($\beta = 0.317, p < 0.001$) and personal innovativeness in the domain of health technology ($\beta = 0.262, p < 0.001$) also significantly contribute to *reasons for*, suggesting that consumers who perceive themselves as progressive or willing to experiment with new technologies are more inclined to construct favorable reasoning toward AIMDSS. For the *reasons against* construct, traditional self exerts the most substantial influence ($\beta = 0.821, p < 0.001$), underscoring the role of cultural adherence to conventional norms and skepticism toward technological change. Perceived threat also significantly contributes ($\beta = 0.31, p = 0.004$), reflecting concerns about the potential negative impacts of AI on human uniqueness or safety. All outer weights are statistically significant ($p < 0.05$), demonstrating that each lower-order component (LOC) is a meaningful contributor to its respective higher-order construct. Notably, the stronger weights of Initial Trust and Traditional Self underscore their central roles in shaping *reasons for* and *against* AI adoption in healthcare, respectively. This supports the validity of the reflective–formative model and justifies the use of these constructs in the structural model (Becker, Klein and Wetzels, 2012).

Table 3.19. Results on the outer weights

	Coeff.	P values
Initial trust -> Reasons for	0.654	0
Modern self -> Reasons for	0.317	0
Personal innovativeness in the domain of health technology -> Reasons for	0.262	0
Perceived threat -> Reasons against	0.31	0.004
Traditional self -> Reasons against	0.821	0

Direct effect testing

To evaluate the magnitude and statistical significance of the structural path coefficients, the author conducted a bootstrapping procedure using 5,000 resamples,

with a two-tailed test at a 0.05 significance level. The detailed results of the hypothesis testing are reported in Table 3.20. Among the eleven proposed hypotheses, eight were supported based on statistical significance ($p < 0.05$), while three were not supported. Attitude toward AIMDSS demonstrated a strong and significant positive effect on intention to adopt ($\beta = 0.453$, $p < 0.001$, $f^2 = 0.255$), supporting H1. Both reason constructs showed differential impacts: reasons for adoption significantly influenced both intention ($\beta = 0.397$, $p < 0.001$, H2) and attitude ($\beta = 0.749$, $p < 0.001$, H4), with large effect sizes, while *reasons against* adoption negatively affected attitude ($\beta = -0.120$, $p = 0.003$, H5), though its direct effect on intention was nonsignificant ($\beta = 0.016$, $p = 0.652$, H3), indicating a potential mediating role of attitude. Regarding antecedents of reasoning, techno-optimism significantly increased both *reasons for* ($\beta = 0.609$, $p < 0.001$, H6) and *reasons against* ($\beta = 0.284$, $p < 0.001$, H7), although its direct effect on attitude was not statistically significant ($\beta = 0.079$, $p = 0.092$, H8). Similarly, anthropocentrism was positively associated with both *reasons for* ($\beta = 0.255$, $p < 0.001$, H9) and *reasons against* ($\beta = 0.409$, $p < 0.001$, H10), but did not significantly influence attitude directly ($\beta = -0.027$, $p = 0.478$, H11). These findings align with the theoretical assumptions of Behavioral Reasoning Theory (Westaby, 2005), underscoring the critical role of context-specific reasons in shaping attitudes and intentions, while also highlighting the indirect influence of individual beliefs on adoption decisions.

Table 3.20. Direct effects (baseline model)

First-order estimate paths	Path Coeff.	f2	p-value	Hypothesis	Results
Direct effects					
Attitude -> Intention	0.453	0.255	0	H1	Supported
Reasons for -> Intention	0.397	0.158	0	H2	Supported
Reasons against -> Intention	0.016	0.001	0.652	H3	Not supported
Reasons for -> Attitude	0.749	0.535	0	H4	Supported
Reasons against -> Attitude	-0.12	0.02	0.003	H5	Supported
Techno-optimism -> Reasons for	0.609	0.715	0	H6	Supported
Techno-optimism -> Reasons against	0.284	0.104	0	H7	Supported
Techno-optimism -> Attitude	0.079	0.007	0.092	H8	Not supported
Anthropocentrism -> Reasons for	0.255	0.125	0	H9	Supported
Anthropocentrism -> Reasons against	0.409	0.217	0	H10	Supported
Anthropocentrism -> Attitude	-0.027	0.001	0.478	H11	Not supported

Indirect effect testing

Table 3.21 presents the results of the mediation analysis examining the indirect effects of techno-optimism and anthropocentrism on intention to adopt AIMDSS through attitudinal and reasoning pathways. The direct mediating role of attitude alone was not statistically significant for either techno-optimism ($\beta = 0.036$, $p = 0.106$) or anthropocentrism ($\beta = -0.012$, $p = 0.486$), suggesting that attitude does not independently transmit the effect of these antecedents to intention. However, significant serial mediation pathways emerged when incorporating the reasoning constructs. Specifically, techno-optimism exerted a strong positive indirect effect on intention via reasons for adoption and attitude ($\beta = 0.207$, $p < 0.001$), while also displaying a small but significant negative indirect effect through reasons against and attitude ($\beta = -0.015$, $p = 0.016$). Similarly, anthropocentrism showed a significant positive indirect effect through *reasons for* and attitude ($\beta = 0.087$, $p < 0.001$) and a negative indirect effect through *reasons against* and attitude ($\beta = -0.022$, $p = 0.012$). These findings align with the propositions of Behavioral Reasoning Theory (Westaby, 2005), highlighting that the influence of beliefs on behavioral intentions is primarily channeled through context-specific reasoning and attitudinal evaluations.

Table 3.21. Indirect effects

	Coeff.	P values
Techno-optimism -> Attitude -> Intention	0.036	0.106
Anthropocentrism -> Attitude -> Intention	-0.012	0.486
Techno-optimism -> Reasons for -> Attitude -> Intention	0.207	0
Techno-optimism -> Reasons against -> Attitude -> Intention	-0.015	0.016
Anthropocentrism -> Reasons for -> Attitude -> Intention	0.087	0
Anthropocentrism -> Reasons against -> Attitude -> Intention	-0.022	0.012

Extended model (with control variables)

When control variables were incorporated into the model, the explanatory structure of intention to adopt medical AI remained broadly consistent with the baseline model, thereby underscoring the robustness of the hypothesised relationships. The direct effects of attitude ($\beta = 0.271$, $p < 0.001$) and reasons for adoption ($\beta = 0.254$, $p < 0.001$) on intention remained significant. However, their effect sizes decreased compared to the baseline model ($\beta = 0.453$ and $\beta = 0.397$, respectively). Similarly, *reasons against* adoption continued to exert no significant influence on intention ($\beta = -0.006$, $p = 0.854$),

consistent with the baseline result ($\beta = 0.016$, $p = 0.652$). Notably, while the baseline model indicated a marginally positive but insignificant association, the extended model revealed a negative direction, which is more theoretically consistent with the BRT framework, although the effect remained non-significant. These findings suggest that the main theoretical relationships proposed in the baseline model are not substantially altered when additional variables are considered.

At the attitudinal level, the extended model retained the strong positive association between reason for adoption and attitude ($\beta = 0.749$, $p < 0.001$). In contrast, *reasons against* adoption retained its significant negative effect ($\beta = -0.120$, $p = 0.003$). The direct effect of techno-optimism on attitude remained non-significant ($\beta = 0.079$, $p = 0.092$), although its indirect effects via *reasons for* and *against* adoption persisted, as observed in the baseline. Likewise, anthropocentrism continued to significantly predict both reason for ($\beta = 0.255$, $p < 0.001$) and reason against adoption ($\beta = 0.409$, $p < 0.001$), while showing no direct effect on attitude ($\beta = -0.027$, $p = 0.479$). These patterns align closely with the baseline findings, supporting the robustness of the proposed belief–reason–attitude pathways.

The inclusion of controls, however, revealed additional determinants of intention. Among the demographic factors, age exhibited a small but significant negative effect ($\beta = -0.076$, $p = 0.013$), suggesting that younger consumers are more inclined to adopt medical AI. Gender also showed a significant effect ($\beta = 0.121$, $p = 0.030$), suggesting that adoption intentions may differ between male and female respondents. By contrast, family income ($\beta = 0.030$, $p = 0.299$) and personal income ($\beta = 0.041$, $p = 0.286$) were not significant predictors. Notably, the inclusion of subjective norms ($\beta = 0.234$, $p < 0.001$) and perceived behavioural control ($\beta = 0.197$, $p < 0.001$), consistent with the reasoning structure of BRT, significantly enhanced the model's explanatory power.

Overall, the extended model confirms the robustness of the baseline findings while refining the picture of consumer adoption of medical AI. The reduction in effect sizes of attitude and reasons on intention after incorporating control variables suggests partial overlap in explanatory power with global motives and demographics, yet the hypothesised relationships remained stable and significant. Notably, the extended model highlights the complementary role of subjective norms and perceived behavioural control, in line with the broader theoretical framework of BRT. The emergence of age and gender effects further contextualises adoption patterns, pointing to socio-demographic sensitivities not captured in the baseline model.

Table 3.22. Direct effects (extended model)

	Path coefficients	P values
Anthropocentrismropocentrism -> Attitude	-0.027	0.479
Anthropocentrism -> Reasons against	0.409	0
Anthropocentrism -> Reasons for	0.255	0
Age -> Intention	-0.076	0.013
Attitude -> Intention	0.271	0
Gender -> Intention	0.121	0.03
Family Income -> Intention	0.03	0.299
Personal Income -> Intention	0.041	0.286
Perceived behavioral control -> Intention	0.197	0
Reasons against -> Attitude	-0.12	0.003
Reasons against -> Intention	-0.006	0.854
Reasons for -> Attitude	0.749	0
Reasons for -> Intention	0.254	0
Subjective norms -> Intention	0.234	0
Techno-optimism -> Attitude	0.079	0.092
Techno-optimism -> Reasons against	0.284	0
Techno-optimism -> Reasons for	0.609	0

SUMMARY OF CHAPTER 3

Chapter 3 presents the full spectrum of empirical findings derived from both qualitative and quantitative phases of the research. The chapter begins with an overview of the qualitative results obtained through semi-structured interviews and focus groups. These exploratory insights uncover key thematic patterns that shed light on consumer perceptions, motivations, and concerns regarding the adoption of AI-enabled medical decision support systems (AIMDSS).

Subsequently, the chapter transitions into the quantitative analysis, which includes a comprehensive examination of the survey data. This section outlines the demographic characteristics of the sample, followed by assessments of the measurement model's reliability and validity, including tests of internal consistency, convergent validity, and discriminant validity. The chapter also presents the outcomes of the structural model evaluation, providing statistical evidence for the hypothesized relationships within the revised research framework. Together, these results provide a solid empirical foundation that supports the study's theoretical propositions.

The chapter concludes by setting the stage for the final discussion in Chapter 4, where the author will interpret the findings in greater depth, linking them to prior literature and research objectives. This forthcoming discussion will also emphasize the study's contributions to the academic understanding of AI adoption in healthcare and outline practical implications for industry stakeholders and policymakers.

CHAPTER 4: DISCUSSION AND IMPLICATIONS

4.1. Discussion

The present study applies the BRT theoretical framework. It employs a mixed-methods approach to explain the significant impact of beliefs (i.e., anthropocentrism and techno-optimism) on reasons and intentions to adopt AIMDSS. The results of this study demonstrate several valuable findings. Notably, the employment of a preliminary qualitative study helps enrich understanding of the state of medical AI adoption in a developing country, with Vietnam as an example. More importantly, this qualitative approach unveils factors that constitute the rationales for and against the consumers' adoption of medical AI. Based on the reasons extraction and hypotheses specification in the preliminary study, this study examined a comprehensive framework from a behavioral rationality perspective to understand the *reasons for* and *reasons against* adopting AIMDSS of consumers. Specifically, initial trust, modern self, and personal innovativeness in the domain of health function as subconstructs of *reasons for* adopting AIMDSS. Meanwhile, traditional self and perceived threat as subconstructs of *reasons against* have significant adverse effects on AIMDSS adoption. The results supported the conclusion that beliefs (i.e., anthropocentrism and techno-optimism) have substantial influence on reasons for and against, as well as on attitudes toward, AIMDSS. While *reasons for* are observed to have a direct and substantial effect not only on users' attitudes but also on their intentions to adopt AIMDSS, reasons against exert only a significant negative impact on attitude but no significant impact on consumers' intentions. Thus, the insignificant effect of *reasons against* on intention is in contrast with the findings of previous studies (Wagner and Westaby, 2020; Ahmad and Harun, 2023; Li and Wang, 2024), but consistent with findings of Claudy et al. (2015). The findings suggest that both anthropocentric and techno-optimistic consumers are inclined to adopt medical AI. However, the underlying motivational structures differ between the two groups. For techno-optimistic consumers, the reasons in favour of adoption outweighed those against, whereas for anthropocentric consumers, the reasons against adoption outweighed those for.

4.1.1. *The current status of medical AI adoption in Vietnam*

The exploratory phase demonstrates that medical AI adoption in Vietnam is still at a nascent stage. Findings reveal the uneven penetration across settings, with earlier and more agile uptake in private hospitals and large urban centers, and limited or largely demonstrative use in public and provincial facilities. This finding reinforces earlier

observations on the embryonic stage of medical AI adoption in Vietnam (Vuong *et al.*, 2019; Chanh *et al.*, 2023) and aligns with evidence of uneven AI implementation across healthcare systems in low- and middle-income countries (Zuhair *et al.*, 2024; Wibowo *et al.*, 2025). Such inadequate infrastructure may result in uneven quality and access to healthcare (Wibowo *et al.*, 2025), thereby limiting consumers' exposure to medical AI. As a result, consumers may have a limited understanding of how medical AI systems function, leading them to base their adoption intentions primarily on other factors, such as their underlying beliefs.

Subsequently, findings from both semi-structured interviews and focus groups indicate a generally positive attitude toward AI and digital transformation. However, both informants and focus group participants show a strong preference for AI as a supportive role rather than as a replacement for human doctors in medical services. Findings from this phase also help probe the context-specific reasons underlying consumers' intention to adopt medical AI. Specifically, the qualitative analysis revealed a set of emerging themes that participants invoked as rationales in discussing medical AI adoption. Initial trust in medical AI, modern self, and personal innovativeness in health were identified as reasons for adoption. In contrast, identity threat, realistic threat, and traditional self surfaced as reasons against it. These reasons were consistently expressed across informants and focus group participants and were closely tied to beliefs of anthropocentrism and techno-optimism. This supports BRT (Westaby, 2005), which posits that beliefs provide the foundation for reasons 'for' and 'against' adoption.

4.1.2. The influence of global motives on intention to adopt medical AI

The results highlighted the importance of attitude, which significantly and positively influenced behavioral intention, aligning with extensive evidence in existing technology acceptance literature (Venkatesh, Thong and Xu, 2012; Li and Wang, 2024). The strong predictive power of attitude supports Westaby's (2005) original proposition within BRT, affirming attitude as global motives crucial to the intention formation process. Mixed-methods findings consistently show that consumers tend to express generally positive but conditional attitudes toward clinical AI supporting use in many scenarios yet insisting on human oversight, transparency, and accountability (Young *et al.*, 2021; Fritsch *et al.*, 2022). In both qualitative and quantitative findings, positive attitudes of consumers are tempered by their *reasons against*, specifically perceived threats and traditional self. Still, the overall valence is favourable, which makes an Attitude → Intention effect theoretically and empirically plausible in consumer samples. This finding is consistent with a previous BRT study of Li and Wang (2024), which

found that consumers' favourable attitude toward AI-assisted diagnostic systems significantly enhanced their adoption intention. Hajiheydari et al. (2025) also reported similar findings in patients evaluating AI diagnosis.

In addition to attitude, other global motives in this study, namely perceived behavioral control and subjective norms, were also found to exert a positive influence on consumers' adoption intentions. This finding is consistent with both the TPB (Ajzen, 1991) and BRT (Westaby, 2005). Subjective norm significantly predicted intention ($\beta = 0.234$, $p < .001$), suggesting that consumers' decisions to adopt medical AI are shaped not only by their personal evaluations but also by the expectations and approval of significant others. This is consistent with prior research showing that normative pressure from family, peers, and especially healthcare professionals exerts a strong influence on willingness to engage with AI-enabled health services (Young *et al.*, 2021). Similarly, perceived behavioral control was also significant ($\beta = 0.197$, $p < .001$), indicating that consumers' belief in their capacity and resources to use medical AI technologies is an important determinant of intention. Hajiheydari et al. (2025) found that patients' confidence in their ability to use AI diagnosis was a significant motivator. Taken together, these results underscore that attitude remains the strongest predictor of intention to adopt novel technologies such as medical AI in healthcare, even after accounting for other global motives.

4.1.3. The influence of reasons on intention to adopt medical AI

4.1.3.1. The influence of reasons for

In BRT, reasons are the proximal, content-rich justifications that bridge beliefs to global motives and behavior (Westaby, 2005). Reasons for adopting AIMDSS, comprising initial trust, modern self, and personal innovativeness in the domain of health technology, emerged as significant determinants of both attitudes and intentions. The second-order estimated path supported the appropriateness of measuring reasons for these constructs, as all paths were statistically significant. These findings support Agarwal and Prasad's (1998) arguments about personal innovativeness as a critical driver of technological adoption, especially in healthcare contexts where innovation is closely associated with health outcomes (Fan *et al.*, 2020). Similarly, the role of initial trust as an antecedent of technology acceptance resonates with existing empirical evidence, underscoring its foundational role in consumer–technology relationships, especially in sensitive domains such as healthcare (Gefen, Karahanna and Straub, 2003; Söllner, Hoffmann and Leimeister, 2016; Jain, Wadhwani and Eastman, 2024). The

modern self-concept, reflecting a desire to identify with contemporary lifestyles and openness to innovation, further underlines the relevance of consumer identity in shaping technology acceptance.

The findings revealed substantial positive impact of reasons for on both intention and attitude, lending support to hypotheses 2 and 4. Also, these findings provide further support for the significant positive relationships between reasons for and attitude, as well as reasons for and intention, consistent with previous studies (Claudy et al., 2013; Li and Wang, 2024; Wagner and Westaby, 2020). Whereas, this finding is contrast with the previous finding of Claudy et al. (2015) which suggest the no significant relationship between *reasons for* and intention. This comparison is only relative, as reasons are context-dependent, and the reasons employed in studies applying BRT differ across contexts (Westaby, 2005). The strong positive links from *reasons for* to attitude and from *reasons for* to intention appear contingent on the constituent enablers that supply the content of those reasons, notably initial trust, personal innovativeness in the health domain, and a modern self. These findings support prior evidence that higher levels of consumers' initial trust are associated with more favorable evaluations of medical AI and a greater willingness to use it (Nadarzynski *et al.*, 2019; Young *et al.*, 2021; Li and Wang, 2024). Personal innovativeness in the health domain predisposes consumers to evaluate novel medical technologies as attractive and workable, thereby increasing the persuasive force of reasons for and strengthening their effects on both attitude and intention. These findings are consistent with prior studies showing that consumers with higher personal innovativeness report stronger purchase intentions for novel health products (Zhang *et al.*, 2017; Jeong and Choi, 2022), likely because they ascribe higher social image benefits and perceive greater novelty, aesthetic appeal, and relative advantage (Jeong and Choi, 2022). Following Nguyen et al. (2009), the modern self reflects individuals' adherence to imported values, norms, and beliefs in transitional Asian markets and is commonly associated with openness to new products, experiences, and change, as well as a lifestyle. In this study, the modern self emerges as a strong factor of reasons for adopting medical AI. The results indicate that consumers tend to align with their self-concept, so those with a modern self-concept exhibit more positive attitudes and stronger intentions to adopt novel technologies, such as medical AI.

4.1.3.2. The influence of reasons against

The modest negative effect of reasons against on attitude (H5), together with the non-significant direct effect on intention (H3), contrasts with prior studies that report a significant negative relationship between reasons against and intention (Ahmad and

Harun, 2023; Li and Wang, 2024; Wagner and Westaby, 2020). However, these findings are consistent with Claudy et al. (2015), who suggest that consumer resistance to innovation often operates indirectly by shaping unfavorable attitudes rather than triggering immediate behavioral avoidance. Reasons against medical AI adoption, comprising traditional self and perceived threats, showed no significant direct effect on intentions but negatively influenced attitudes. Thus, reasons against adoption likely represent attitudinal barriers rather than direct impediments to intended behavior, aligning with prior innovation resistance literature (Heidenreich and Handrich, 2015). Further, it should be noted that reasons are context-specific, thus, reasons against across contexts are different. Therefore, factors constituting *reasons against* medical AI adoption should be considered to justify this result. In this study, perceived threat consists of identity threat and realistic threat. Identity threat captures the feeling that medical AI diminishes human distinctiveness, professional judgment, or the relational quality of care. Realistic threats capture concrete risks such as diagnostic errors, bias, privacy breaches, and safety failures. These threat-based cognitions load into the reasons against construct and, in line with BRT, depress consumers' attitudes. This is visible in the significant negative path from reasons against to attitude ($\beta = -0.120$, $p = 0.003$). By contrast, the direct path from reasons against to intention is statistically null ($\beta = -0.006$, $p = 0.854$). Although AIMDSS is designed as an assistive form of medical AI, consumers may still perceive both identity threat and realistic threat, particularly in the high-stakes context of healthcare. When medical AI is cognitively categorized as an out-group relative to humans, it heightens sensitivity to identity-related concerns, including perceived threats to human expertise, professional authority, and the irreplaceability of human judgment. In addition, patients may be concerned about the erosion of human identity in healthcare, which has traditionally been grounded in the relational bond between healthcare professionals and patients, encompassing not only disease treatment but also empathy, emotional support, and moral care. At the same time, realistic threat arises from concerns about tangible risks associated with AI use, including diagnostic errors, system malfunction, data bias, safety issues, and unclear accountability when AI-supported decisions lead to adverse outcomes. Concerns about unclear accountability when AI-supported decisions lead to adverse outcomes further reinforce perceptions of realistic threat. As a result, even when consumers acknowledge the potential benefits of AIMDSS, these perceived threats can reduce receptivity or temper otherwise positive attitudes toward its adoption. Regarding the traditional self, this result aligns with evidence that individuals who identify as traditional are cautious toward new products and services (Nguyen, Smith and Cao, 2009; Nguyen *et al.*, 2019).

Consequently, a completely novel offering such as medical AI is less likely to be evaluated positively by traditional consumers, particularly in the sensitive healthcare context. The insignificant path Reasons against → Intention suggested the direct influence is not supported; instead, their influence is transmitted through attitude.

4.1.4. The role of beliefs in determining intention to adopt medical AI

Techno-optimism and anthropocentrism both positively influenced reasons for and against adoption. The dual impacts of techno-optimism, capturing consumers' simultaneous recognition of technology's benefits and potential downsides, suggest that optimism toward technology does not preclude acknowledgment of risks, but instead promotes balanced consideration. Likewise, anthropocentrism's influence on both sets of reasons corroborates the dual nature of consumer beliefs: anthropocentric consumers may embrace AI that enhances human capabilities yet remain wary of perceived threats to human uniqueness (Kaplan and Haenlein, 2020; Belanche, Casaló and Flavián, 2021).

4.1.4.1. The direct effects of beliefs on attitude and reasons

This study finds that techno-optimism does not exert a significant direct effect on consumers' attitudes toward adopting AIMDSS in the Vietnamese context. This result diverges from prior studies that report a positive relationship between techno-optimism and favorable attitudes toward emerging technologies, such as augmented reality in education (Álvarez-Marín, Velázquez-Iturbide and Castillo-Vergara, 2023) and smart home technologies (Leung and Cheung, 2025). It is not anomalous when seen in light of studies where optimism does not translate directly into core evaluations once more proximal appraisals are modelled. A plausible explanation lies in the high-stakes and trust-sensitive nature of healthcare decision-making, where general optimism toward technology may be insufficient to directly shape attitudes toward AI-supported medical decisions. From a Behavioral Reasoning Theory perspective, techno-optimism may instead operate indirectly by influencing context-specific reasons for or against adoption, rather than functioning as a direct attitudinal antecedent. In addition, the Vietnamese healthcare context, characterized by strong reliance on physician authority and limited direct patient interaction with medical AI, may further attenuate the direct translation of techno-optimism into positive attitudes toward AIMDSS. Blut and Wang (2020) suggest that technology readiness motivators, such as optimism, do support technology use, but mostly by shaping intermediate evaluations (perceived quality, value, usefulness, etc.), rather than through a strong, universal direct effect on use or attitudes. Jan et al. (2023) conceptualise technology optimism as part of the broader category of technology-readiness motivators and demonstrate that these motivators

shape individuals' reasons for using AI chatbots. Their model does not include a direct pathway from optimism to attitude. Instead, they show that optimism strengthens reasons for adoption, and that these reasons subsequently exert a substantial effect on attitudes and behavioural intentions. This structure reflects a view of techno-optimism as a distal readiness factor whose influence is channelled through context-specific justifications rather than through an immediate evaluative response. That insight helps explain the non-significant effect of techno optimism on attitudes in the present study (H8). Once reasons for and against adopting AIMDSS are included in the model, the impact of general optimism toward technology is mainly absorbed by these mediating mechanisms. Jan et al. (2023)'s findings therefore support the interpretation that techno-optimism contributes to overall adoption. Still, its role is expressed indirectly through the formation of reasons rather than through a substantial direct effect on attitudes. This pattern aligns with the assumptions of BRT, which posits that broad beliefs are distal antecedents that influence attitudes only after individuals articulate concrete reasons relevant to the decision context.

In the AI adoption literature, anthropocentrism is frequently characterised as a belief that privileges human agency, authenticity, and control. This orientation often leads individuals to view AI systems as encroaching on domains that should remain fundamentally human, thereby fostering scepticism and negative attitudes toward AI-enabled solutions. Empirical studies have shown that individuals with strong anthropocentric beliefs tend to perceive AI as a threat to human uniqueness, moral agency, or professional expertise (Fortuna, Wróblewski and Gorbaniuk, 2023; Fortuna *et al.*, 2024). These perceptions can generate concerns about loss of control or dehumanisation, which directly reduce favourability toward AI-based decision tools. However, as a supporting tool such as AIMDSS, this study hypothesized that anthropocentric people may perceive this system more favourably as they consider it serves their needs, thus reinforcing humans' central role (H11). However, the results showed that this direct effect was not statistically significant. This outcome is not entirely surprising when interpreted through the lens of Behavioral Reasoning Theory. Previous BRT studies have shown that distal antecedent, such as value, exert a non-significant direct effect on attitude (Ahmad and Harun, 2023; Pillai *et al.*, 2023; Wagner and Westaby, 2020; Claudy, Garcia and O'Driscoll, 2015; Claudy, Peterson and O'Driscoll, 2013). Thus, it would be reasonable that distal beliefs, such as anthropocentrism, may not directly shape attitudes once individuals begin to evaluate the behaviour through context-specific reasons. In other words, although anthropocentric individuals may hold strong human-centred

beliefs, these beliefs influence attitudes primarily through concrete reasoning. The non-significant direct effect found in this study therefore suggests that anthropocentrism exerts its influence indirectly, by shaping the reasons for/ against adoption, which subsequently drive attitudes. Given that empirical evidence on the relationship between anthropocentrism and attitude within this framework is currently lacking, this study is among the first to examine the role of anthropocentric belief through the lens of BRT. Thus, future studies should re-examine the relationship between belief and attitude within the BRT framework.

4.1.4.2. The indirect effects

The mediation analysis significantly enriched our understanding by highlighting that techno-optimism and anthropocentrism indirectly shaped behavioral intentions through reasons and attitudes. The nonsignificant mediating role of attitudes alone underscores the criticality of integrating specific reasons, supporting Westaby (2025)s' recent suggestion for expansion of BRT. The significant serial mediation (techno-optimism → *reasons for* adoption → attitudes → intention) reinforces the theoretical assertion that consumers' overarching positive beliefs about technology (techno-optimism) influence intentions primarily through the formulation of context-specific positive reasoning, as discussed by Westaby et al. (2025).

Furthermore, the small but significant negative indirect effect (techno-optimism → reasons against → attitudes → intentions) shows that even generally positive beliefs about technology can still produce subtle countervailing pressures that dampen adoption. This pattern underscores the complex ways in which beliefs translate into behavior, consistent with the Belief-to-Behavior Inference (BBI) model proposed by Granados Samayoa and Albarracín (2025). According to BBI, consumers actively engage in comparative reasoning processes, balancing positive beliefs against potential drawbacks (Granados Samayoa and Albarracín, 2025). The findings thus empirically illustrate this dynamic cognitive balancing act, demonstrating that techno-optimistic consumers do not ignore potential risks; rather, they integrate both favorable and unfavorable beliefs into their ultimate intention formation.

Anthropocentrism also exerted dual indirect effects, revealing that this belief can simultaneously activate mechanisms that encourage and discourage adoption, rather than pushing behavior in a single direction. Anthropocentric consumers positively embraced AIMDSS when perceived as supportive of human roles (positive indirect path), yet simultaneously expressed significant reservations regarding threats to human identity and traditional values (negative indirect path). Such dual reasoning echoes

recent conceptualizations of human–AI interactions, emphasizing consumer ambivalence toward technology that intersects with core human values and identities (Belanche, Casaló and Flavián, 2021; Huang and Rust, 2021a).

In summary, this study advances understanding of how consumers’ specific beliefs (i.e. anthropocentrism and techno-optimism) shape behavioral intention through context-specific reasoning processes. Consistent with prior BRT research, the findings confirm a strong positive relationship between reasons for and both attitude and intention to adopt AIMDSS (Claudy et al., 2013; Li and Wang, 2024; Wagner and Westaby, 2020). However, in contrast to Li and Wang (2024), who report a significant negative effect of reasons against on Chinese consumers’ intention to adopt AIMDSS, this study finds that reasons against do not exert a significant direct effect on intention in the Vietnamese context. Instead, reasons against influence intention indirectly through attitudes, while underlying belief constructs exert positive and significant effects on both reasons for and reasons against. This pattern is fully consistent with BRT, which posits that beliefs do not influence behavioral intention directly, but operate through context-specific reasons that translate beliefs into attitudinal evaluations and intention (Westaby, 2005, 2025).

4.2. Theoretical contributions

In this dissertation, the author addresses a gap in the existing literature on the adoption of AI-based Medical Decision Support Systems (AIMDSS), where limited research has examined the influence of beliefs, specifically anthropocentrism and techno-optimism, on consumers’ behavioral intentions to adopt such systems. The findings contribute to a deeper understanding of consumer adoption of medical AI by focusing on AIMDSS as a technological breakthrough in the healthcare industry and by exploring the roles of both facilitating and inhibiting factors within the proposed theoretical framework (Prakash and Das, 2021; Li and Wang, 2024). To the author’s knowledge, this dissertation is among the first to investigate the combined effects of dual belief systems, anthropocentrism, and techno-optimism, on consumers’ intentions to adopt AIMDSS through the lens of their underlying reasoning. Thus, this research responds to calls for further exploration of belief-to-behavior relationships by applying Behavioral Reasoning Theory (BRT) to explain consumers’ reasoning pathways toward adoption (Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025).

First, this dissertation makes a specific theoretical move by treating anthropocentrism and technology optimism as co-existing beliefs that jointly shape

consumers' reasons for and against adopting AIMDSS. Furthermore, this dissertation extends BRT application by explicitly examining the impact of these dual beliefs rather than a single belief construct. Specifically, individuals' beliefs (i.e., anthropocentrism and techno-optimism) both positively predict reasoning (for and against) adopting AIMDSS. This pattern contrasts with previous BRT-based research, which has predominantly examined the influence of values on behavioral intention (Westaby, Rosemarino and Elliot, 2025; Li and Wang, 2024; Sahu, Padhy and Dhir, 2020). Prior studies typically report asymmetric effects, in which certain values strengthen reasons for adoption while weakening reasons against (or vice versa) for various services, including medical AI (Li and Wang, 2024; Sahu, Padhy and Dhir, 2020; Ahmad and Harun, 2023; Ashfaq et al., 2021; Claudy, Garcia and O'Driscoll, 2015). In contrast, this dissertation is among the first to investigate the role of beliefs within the BRT framework, given limited attention on this relationship (Granados Samayoa and Albarracín, 2025; Westaby, Rosemarino and Elliot, 2025). Further, the results demonstrate that these beliefs simultaneously enhance both supportive and opposing reasons for AIMDSS adoption. Moreover, results suggest that the magnitude of these effects differs across beliefs. For techno-optimism, its influence on reasons for adoption outweighs its influence on reasons against adoption, suggesting that techno-optimism primarily facilitates acceptance. Anthropocentrism shows the opposite pattern: although it increases both sets of reasons, its more substantial effect on reasons against indicates that anthropocentrism ultimately acts as a barrier to adoption. Individuals with a human-centric worldview are more sensitive to inhibiting factors triggered by automation in healthcare, leading them to place greater emphasis on reasons against the use of medical AI. Conversely, techno-optimists assign greater weight to reasons supporting adoption, as they are predisposed to view technological advancements as beneficial and capable of generating positive outcomes in everyday life, including healthcare. Moreover, the validated serial mediation (belief → reason → attitude → intention) highlights the importance of reasoning as a cognitive bridge between belief and behavior, offering a refined theoretical lens for understanding technology adoption. It supports the belief-to-behavior inference of Samayoa and Albarracín (2025) by showing that anthropocentric belief and techno-optimistic belief do not directly shape adoption intention but instead exert their influence through context-specific reasons, which subsequently inform attitudinal evaluations and intentional outcomes.

Second, this dissertation contributes to the extant literature on determinants of intention to adopt medical AI of consumers by unveiling context-specific set of reasons for/against the adoption of medical AI. Previous studies on this matter have focused on

a value-relevant set of factors. Li and Wang (2024) investigated the impact of value (i.e., openness to change) on medical AI adoption of Chinese consumers, and found strong support for reasons for (including initial trust, health information accessibility, professional level and perceived informational support), and reasons against (privacy concern, uniqueness neglect, health information evaluation and utilization, and information quality). In contrast, this dissertation with the focus on beliefs (i.e., anthropocentrism and techno-optimism), has found that reasons for adopting AIMDSS of consumers in the Vietnamese healthcare context are initial trust, personal innovativeness in the domain of health technology, and modern self; whereas reasons against consist of perceived threats and traditional self via a mixed-method approach. This result reinforces the evidence suggesting the important role of initial trust of consumers in facilitating medical AI adoption, lending support to previous findings (Frank *et al.*, 2021; Gaczek *et al.*, 2023; Kumar, Vrontis and Pallonetto, 2024; Li and Wang, 2024). Also, this dissertation is the first to consider personal innovativeness in the domain of health technology as an important factor in consumers' adoption of medical AI. While previous studies have examined the impact of personal innovativeness in the domain of information technology on doctors' adoption of medical AI (Fan *et al.*, 2020; Tran *et al.*, 2021), it would be a shortcoming to assume that consumers who are innovative in using information technology would keep their stance in healthcare, a domain where their health is at stake. In other words, one may be open and inclined to adopt new technology in general (e.g., ChatGPT, metaverse, Siri, etc.), but may not be as open to novel health technologies such as AIMDSS. Thus, the measurement of PIHT has been adapted to capture the innovativeness of individuals not only in technology but in health technology, an aspect that is more critical as it could have adverse effects on their lives. Thus, integration of this factor in reasons for would be another contribution of this dissertation. Regarding perceived threats, the literature suggests that both identity threats and realistic threats negatively influence attitudes toward and intentions to adopt AI (Złotowski, Yogeewaran and Bartneck, 2017; Cunneen, Mullins and Murphy, 2019; Huang *et al.*, 2021). This study corroborates these findings by showing that these threat perceptions form strong reasons against adopting medical AI. Furthermore, the substantial positive impact of anthropocentrism on reasons against indicates that anthropocentric individuals are particularly sensitive to such threats, as they tend to interpret AI-driven automation as undermining human expertise, diminishing the role of clinicians, and encroaching on the uniquely human elements of care. Consequently, anthropocentrists are more likely to amplify concerns about loss of control, reduced human judgment, and potential harm arising from delegating decision-

making to machines, even though AIMDSS serve as a supporting tool to humans. Thus, this finding enriches the understanding of how anthropocentrism may activate consumer resistance, explicitly through perceived identity and realistic threats.

Another contribution to the medical AI adoption literature is the incorporation of self-concepts as reasons for/against consumers' behavioral intention to adopt novel technology such as AIMDSS. Transitional economies such as Vietnam provide a unique sociocultural setting in which individuals simultaneously draw on both a modern self, characterized by openness to innovation, autonomy, and forward-looking identities, and a traditional self that emphasizes conformity, risk aversion, and reliance on established norms. Thus, these dual self-concepts may shape how consumers evaluate emerging technologies like AIMDSS, making them either more receptive to or more hesitant about adoption. Despite their theoretical relevance, self-concepts have mainly been examined in the domains of organic food consumption and travel behaviour (Huang, LeBlanc and Choi, 2016; Nguyen et al., 2019). Thus, this study revisits the concept and provides empirical evidence that the modern self and the traditional self, respectively, serve as strong reasons for and against adoption. This finding adds conceptual depth to the literature and highlights the importance of sociocultural identity in shaping responses to AI in healthcare.

Lastly, the findings provide theoretical insights into the role of anthropocentrism in the technology adoption literature. Historically, anthropocentric beliefs have predominantly been examined as impediments to AI acceptance due to their emphasis on human centrality and uniqueness (Kaplan and Haenlein, 2020; Huang and Rust, 2021b). However, this dissertation presents a different theoretical position, revealing that anthropocentrism can simultaneously facilitate and hinder adoption, contingent on how the technology is cognitively framed (human-enhancing vs. human-replacing). Such dual roles resonate with the "technology paradox" articulated by Mick and Fournier (1998), in which technology simultaneously embodies potential for consumer empowerment and threats to consumer well-being. Therefore, this research contributes theoretically by expanding the conceptual boundaries of anthropocentric beliefs within consumer behavior literature, highlighting their context-sensitive ambivalence rather than a monolithic negative stance toward technological innovations. (Heidenreich and Handrich, 2015; Belanche, Casaló and Flavián, 2021).

4.3. Practical implications

Building on the empirical findings, this section translates the research model into concrete and feasible AI adoption strategies for the healthcare sector. The proposed implications are explicitly aligned with (i) hospitals' organizational capabilities and

service quality improvement, (ii) the national digital transformation orientation of the Party and the State, and (iii) the key psychosocial variables in the research model, including techno-optimism, anthropocentrism, reasons for, and reasons against adoption. By structuring the implications across hospitals, medical AI developers, and policymakers, this section aims to enhance the practical relevance and policy applicability of the study's findings.

4.3.1. Implication for hospitals

Firstly, in relation to the techno-optimism construct, which strongly influences reasons for adopting AIMDSS, healthcare providers in developing countries like Vietnam should focus efforts on consumers with high technology optimism, often comprising younger, digitally savvy individuals (Pillai *et al.*, 2023). Hospitals and clinics could practically leverage this by initiating targeted educational and promotional campaigns via digital platforms, such as social media and mobile health apps. Such campaigns should highlight the concrete benefits of AIMDSS, including improved diagnostic accuracy, time savings, and modernized healthcare experiences. Further, implementing a medical AI experience hub within hospitals or community health centers could practically resonate with techno-optimistic segments by allowing first-hand interactions, thereby increasing initial trust (Li and Wang, 2024).

Secondly, recognizing that anthropocentrism simultaneously generates reasons for and against adopting AIMDSS, healthcare administrators and policymakers must carefully frame AIMDSS to effectively target consumer segments that hold human-centered values. These may include older patients and individuals who identify as traditional, who feel more connected to traditional Vietnamese healthcare practices. Practically, healthcare professionals should position AIMDSS explicitly as tools designed to empower rather than replace human physicians, emphasizing human–AI collaboration scenarios (Longoni, Bonezzi and Morewedge, 2019; Belanche, Casaló and Flavián, 2021; Kunz and Wirtz, 2023). For instance, hospitals could explicitly integrate AIMDSS into physician–patient consultations, allowing patients to visually observe how the AI assists medical staff in providing better, patient-centered care. Moreover, engaging respected medical practitioners as ambassadors to advocate for the complementary roles of AIMDSS could reassure patients concerned about threats to traditional human roles. Such authoritative endorsements, accompanied by clear narratives affirming human primacy, would mitigate anthropocentric consumers' identity threats and realistic concerns regarding technology displacing human judgment (Kaplan and Haenlein, 2020; Huang and Rust, 2021b).

Thirdly, the significant negative influence of reasons against adoption (traditional self and perceived threats) on consumer attitudes necessitates targeted practical actions addressing cultural conservatism and technology-related threats prevalent among Vietnamese healthcare consumers. Specifically, leveraging innovative educational approaches, such as visualization videos, can effectively help consumers imagine a future in which AIMDSS is seamlessly integrated into healthcare delivery. By clearly depicting scenarios where AI complements and enhances human medical expertise rather than replacing it, these visualization videos help patients understand the practical benefits and protective measures, thereby alleviating concerns about autonomy and safety. Moreover, creating short video stories featuring older individuals who have had positive experiences with medical AI can help patients connect emotionally with the message. Such testimonials can reframe perceptions, reduce long-standing anxieties, and make the technology feel more relatable and trustworthy. Therefore, combining transparency, participatory design, visualization-driven educational materials, and culturally tailored storytelling represents a comprehensive and engaging strategy for addressing perceived threats, building consumer trust, and fostering broader adoption of AIMDSS in healthcare settings in developing countries.

Fourth, the qualitative findings suggest that both doctors and patients feel insecure about adopting medical AI in the healthcare services due to concern of safety. This is further justified in the robust impact of realistic threat on reasons against adopting AIMDSS of consumers following the survey. Thus, hospitals should develop and disseminate comprehensive guidelines for the use of AI in clinical practice to ensure that both physicians and patients are fully informed. These guidelines should specify how AI systems are integrated into diagnostic and treatment processes, outline the responsibilities of healthcare professionals when using AI support, and clarify patient rights when AI tools are involved. Hospitals should also prepare educational leaflets and communication materials for patients. These materials should explain, in accessible language, the role of AI in the healthcare service, its expected benefits for safety and efficiency, and any potential limitations or risks. Providing transparent and consistent information in this manner can enhance trust, promote informed decision-making, and support the responsible adoption of medical AI in routine care.

In addition, given the existence of traditional self of consumers and the conservative stance of medical experts, hospitals should also consider adopting a gradual integration roadmap for medical AI. Rather than implementing AI systems abruptly, a stepwise approach that begins with small-scale pilots, followed by phased

expansion, allows patients and clinicians to become familiar with the technology and adjust naturally to its presence in routine care. This progressive rollout also provides opportunities to identify operational issues early and refine workflows before full implementation.

Lastly, continuous training for healthcare staff is essential. Physicians, nurses, and support personnel need to understand not only the technical functions of AI systems but also how to communicate clearly with patients about their role, benefits, and limitations. Equipping staff with strong AI literacy and patient centered communication skills helps create a more supportive environment, in which patients feel informed, respected, and confident when engaging with AI-assisted healthcare services.

4.3.2. Implication for medical AI developers

Beyond technical performance and regulatory compliance, medical AI developers can take several additional, consumer-oriented actions to increase adoption. The suggestions below focus on practicality and direct impact on consumer perceptions and behavior.

First, developers can simplify how medical AI is presented to consumers by avoiding overly technical language and reframing AI in terms of tangible patient benefits. Instead of emphasizing algorithms or computational power, communication should focus on outcomes that matter to patients, such as earlier detection, fewer missed diagnoses, shorter waiting times, or better treatment monitoring. Clear and benefit-oriented framing helps consumers understand why AI is relevant to their own health.

Second, developers can design AI systems that actively support shared decision making. For example, AI outputs can be structured to present multiple options or confidence ranges rather than a single definitive recommendation. When patients see that AI supports discussion between themselves and their doctors, rather than replacing clinical judgment, they are more likely to feel respected and willing to engage with the technology. This shared decision-making allowance also helps patient have more understanding and control of their treatment procedure, thus reducing their realistic threat posed by medical AI.

Third, developers can invest in local validation and localization. Demonstrating that AI systems are trained, tested, or calibrated using local patient data and clinical guidelines can significantly improve consumer confidence, particularly in countries like Vietnam where patients may be skeptical of imported technologies. Local language interfaces and culturally appropriate explanations further enhance relevance and trust.

This would be particularly meaningful for more traditional consumers who tend to place greater trust in locally grounded medical practices and may be more cautious toward technologies developed or validated in foreign contexts.

Fourth, developers can work with healthcare providers to lower psychological and experiential barriers by allowing patients to encounter AI in low-risk, familiar settings. Examples include AI assisted health screening programs, follow-up monitoring, or preventive care applications. Early positive experiences in non-critical contexts can normalize AI use and reduce anxiety when it is later applied in more serious clinical situations.

Fifth, developers should collaborate closely with hospitals, clinicians, and patient groups throughout the design process. Early engagement with end users allows developers to identify practical challenges, ethical concerns, and contextual expectations that might not be visible from a purely technical perspective. Co-design processes can ensure that the technology fits naturally into clinical workflows and respects patient needs, cultural norms, and local resource limitations. For services that integrate medical AI, developers should consider adding a patient view mode that allows patients to see what the AI has detected, the estimated accuracy, and a simple explanation, followed by the doctor's final conclusion. This presentation helps patients perceive AI as a supportive companion that offers an additional perspective rather than a replacement for the clinician.

Last, developers can actively involve patients in post-deployment improvement. Simple feedback tools, patient satisfaction surveys, or channels for reporting concerns signal that patient voices matter and that the technology evolves based on real user experiences. This sense of participation can strengthen trust and long-term acceptance. Also, that enables hospitals and developers to continuously refine and improve the service.

4.3.3. Implication for policymakers

The qualitative finding on current status of medical AI adoption in Vietnam has revealed major obstacles for wider implementation of this technology in healthcare services for consumers. To resolve those national level issues, policymakers play a crucial role in enabling responsible and scalable adoption of medical AI in the healthcare sector.

First, a national roadmap for medical AI adoption should be developed to provide a phased and coordinated strategy for implementation across different levels of

hospitals. For Vietnam, such a roadmap should align with the country's ongoing digital transformation in healthcare and clearly identify priority use cases that are both feasible and beneficial under current conditions, such as AI supported image analysis, triage assistance, or chronic disease risk prediction. The roadmap should differentiate adoption timelines across hospital tiers, with central and major urban hospitals serving as early pilot sites to test solutions, refine workflows, and generate evidence before scaling to provincial and district hospitals where resources are more limited. It should also assign specific responsibilities to key stakeholders, including the Ministry of Health for regulatory and data standards, hospitals for implementation and validation, academic institutions for capacity building and evaluation, and industry partners for technical support under transparent and safe standards. Importantly, the roadmap must acknowledge regional disparities in digital infrastructure and workforce capacity, specifying when provincial hospitals should rely on national or regional cloud-based AI platforms rather than maintaining high-cost systems locally. By linking AI adoption to broader investments in electronic medical records, hospital information systems, and internet connectivity, this roadmap would enable Vietnam to advance medical AI in a gradual, realistic, and equitable manner across its diverse healthcare settings.

Second, the establishment of clear legal and regulatory frameworks is essential for reducing uncertainty and ensuring safe use of medical AI. Specifically, policymakers should establish a clear legal framework governing the responsible use of AI in healthcare. Such a framework should define the scope of permissible AI applications in clinical practice, specify standards for accuracy, validation, and data protection, and delineate the respective responsibilities of AI developers, healthcare institutions, and medical professionals. Policymakers should also introduce requirements for transparency, including mandatory disclosure of AI involvement in diagnosis or treatment and clear procedures for obtaining informed consent. In addition, mechanisms for accountability and redress are needed so that patients have clear pathways for reporting concerns or seeking resolution when AI related errors occur. Developing such legislation would provide legal certainty, promote ethical implementation, and safeguard patient rights as AI continues to expand in healthcare settings. Thus, hospitals would have a solid basis for developing internal guidelines for the use of medical AI within their facilities. At the same time, patients would gain greater confidence in services supported by both AI and physicians, even among those who tend to be more traditional or initially concerned about possible threats.

Third, regarding technological infrastructure, policymakers should consider building shared national or regional AI infrastructure that hospitals can access without maintaining costly on-site computing systems. Cloud based tools, centralized data storage, and standardized model updates can reduce operational burdens and allow resource limited hospitals to benefit from high quality AI systems. Also, improving digital and internet infrastructure in provincial hospitals is essential for ensuring that medical AI tools function reliably. Policymakers should prioritize bandwidth upgrades, expand internet coverage through collaboration with telecommunications providers, and support hybrid cloud systems that can operate under unstable connectivity conditions. Strengthening these foundational elements will allow provincial facilities to integrate AI more effectively and equitably.

Fourth, targeted funding schemes are needed to support provincial hospitals where financial constraints often limit access to advanced technologies. Policymakers can allocate dedicated resources for AI related equipment, network upgrades, and cloud access, while also encouraging public and private partnerships to expand financial support for underserved regions. In Vietnam, such schemes are particularly important because provincial and district hospitals often operate with limited budgets and outdated infrastructure, making it difficult for them to participate in digital transformation initiatives. A structured funding mechanism could prioritise hospitals that serve large rural populations, cover essential costs such as hardware procurement, data storage solutions, and secure connectivity, and provide subsidies for staff training on AI supported workflows. Additionally, policymakers could introduce incentive programs for technology firms to collaborate with provincial hospitals through discounted licensing, co investment models, or corporate social responsibility projects aimed at enhancing rural healthcare capacity. International development partners and donor organisations may also be mobilised to support AI readiness activities, especially in regions with significant health disparities. By directing financial resources toward these specific needs, policymakers can help ensure that the benefits of medical AI extend beyond major urban centres and contribute to a more equitable and efficient healthcare system nationwide.

Last, tiered training programs should be implemented to address the variation in medical and IT competencies among healthcare workers, particularly in provincial areas. Training initiatives should include basic digital literacy, foundational AI literacy, and practical guidance on interpreting AI output. A structured and continuous training approach can strengthen readiness and improve the quality of AI supported care.

These policy recommendations are aligned with the Party and State's strategic orientations on national digital transformation and the application of advanced technologies in healthcare, as articulated in Resolution No. 52-NQ/TW (2019) on proactive participation in the Fourth Industrial Revolution, Decision No. 749/QĐ-TTg 2020 on the National Digital Transformation Program to 2025 with orientation toward 2030 (The Prime Minister, 2020), and the Health Sector Digital Transformation Program (Ministry of Health of Vietnam, 2019). In addition, they are consistent with the Government's scheme on developing the application of data on population, identification, electronic authentication data for national digital transformation, as reflected in Decision No. 06/QĐ-TTg, 2022 (The Prime Minister, 2022) and the ongoing National Telemedicine Program of the Ministry of Health. The emphasis on phased adoption, human-centered and physician-led AI deployment, infrastructure investment, and workforce capacity building reflects the State's objective of promoting innovation while ensuring safety, equity, and public trust in healthcare services.

4.4. Limitations and future research directions

Despite important theoretical and practical insights into consumer adoption of AI Medical Decision Support Systems (AIMDSS) in Vietnam, this dissertation is subject to some limitations. First, the demographic composition of both the focus group participants and the survey sample is skewed toward younger individuals, which may limit the generalizability of the findings to older healthcare consumers who typically have more frequent and complex interactions with medical services. Additionally, the uneven proportion of online and offline survey responses represents a potential limitation, as it may have subtly influenced the sample composition by favoring respondents who are more familiar with digital platforms. Consequently, the generalizability of the findings to older or less digitally fluent populations is limited to some extent. Future research should aim to recruit more demographically representative samples across age, digital literacy, and health status to validate the current findings and explore generational differences in reasoning and adoption behavior.

Second, the study was conducted exclusively within the Vietnamese context, a transitional, developing economy with unique socio-cultural, economic, and healthcare system characteristics. Although Vietnam provides a valuable context for examining early-stage medical AI adoption, particularly in public health systems with limited digital maturity, the findings may not generalize to other developing countries with different institutional structures or to developed countries where medical AI is more

advanced and healthcare infrastructure is more digitized. Future cross-national comparative studies, particularly those examining adoption in similar Southeast Asian contexts or in advanced economies, could help validate the model and identify context-specific moderating factors such as regulatory environments, digital infrastructure, or cultural values regarding human–AI interaction.

Third, this dissertation has focused on anthropocentrism in relation to AIMDSS, which represents an assistive form of medical AI. The influence of anthropocentrism on consumers' intention to adopt other categories of medical AI, especially those with anthropomorphic attributes, may differ considerably. This distinction is increasingly relevant as AI technologies evolve from supportive to semi-autonomous and autonomous systems, which may provoke fundamentally different consumer beliefs, threats, and ethical concerns. Future research could expand the model by comparing adoption drivers and resistance factors across assistive versus replacement AI systems in healthcare. For instance, researchers could examine whether anthropocentric beliefs or perceived threats exert stronger deterrent effects in the context of human-replacing AI, and whether trust and techno-optimism retain their predictive power under such conditions.

Also, future research could explore longitudinal designs to assess how reasoning processes and adoption intentions evolve as consumers become more familiar with AIMDSS in real clinical settings. Furthermore, integrating affective or emotional responses (e.g., anxiety, awe, or perceived moral discomfort) into the reasoning framework may provide a deeper understanding of the psychological processes underlying consumer judgments, particularly when the technology challenges core aspects of identity or human roles. Lastly, given the growing use of generative AI in patient-facing tools such as chatbots and symptom checkers, researchers could investigate how reasoning patterns differ across various AI applications, ranging from diagnostic support to patient engagement platforms, thereby offering a more comprehensive picture of consumer attitudes toward the AI-powered transformation of healthcare.

SUMMARY OF CHAPTER 4

In Chapter 4, the author offers an in-depth interpretation of the study's empirical results, extending the analyses introduced in Chapter 3. This chapter discusses the theoretical and practical implications of the findings, contextualizing them within the existing body of literature discussed earlier in the dissertation. By systematically linking the results to prior research, the author highlights how the current study advances understanding, particularly in the domain of AI adoption in healthcare by providing novel insights and addressing previously unexplored dimensions. The chapter also underscores the study's unique contributions to the emerging field of medical AI adoption, both in theoretical enrichment and in applied relevance. Furthermore, it revisits the research objectives and questions outlined at the outset, demonstrating how the findings respond to these aims and contribute to a clearer, more comprehensive understanding of consumer behavior toward AI technologies in healthcare. Through this integrated discussion, the chapter consolidates the study's overall contribution and its value for academic and policy-oriented discourse.

CONCLUSION

Understanding consumer adoption of medical AI is particularly critical in transitional economies such as Vietnam, where digital healthcare is still in the nascent stage. This dissertation applies Behavioral Reasoning Theory to explore how diverse belief systems shape intentions to adopt AIMDSS. The Vietnamese cultural context, characterized by the coexistence of dual self-concepts, increasing digital literacy, and growing healthcare demands, offers a compelling backdrop for investigating both supportive and resistant psychological mechanisms. The findings reveal that *reasons for* adoption, such as initial trust, modern self-concept, and personal innovativeness in health technology, significantly promote positive attitudes and strengthen intention to adopt. In contrast, *reasons against*, particularly rooted in perceived threats and traditional self-orientations, act as barriers to favorable attitude formation. The central role of attitude as a mediating global motive highlights its importance in translating belief structures into behavioral intention. These results underscore the need to account for the psychological tension between progressive and conservative belief systems in technology acceptance research.

This dissertation contributes to the literature by extending BRT to the emerging domain of medical AI, offering a belief-based perspective that unpacks the coexistence of facilitating and inhibiting forces in consumer reasoning. The dual role of belief constructs such as techno-optimism and anthropocentrism, acting as antecedents to both “reason for” and “reason against” dimensions, illustrates the complexity of adoption behavior in morally and technologically sensitive domains. From a practical standpoint, the findings emphasize the importance of trust-building, personalization, and belief alignment in promoting the use of AI in healthcare settings. For healthcare providers, policymakers, and technology developers, particularly in emerging markets, these insights suggest that promoting AI adoption requires more than showcasing functional benefits. It also involves addressing concerns about cultural identity and ethical apprehensions. Future research could build on this foundation by exploring cross-cultural comparisons, longitudinal shifts in reasoning patterns, or the role of generative AI tools in influencing trust and personalization in digital healthcare ecosystems.

**RESEARCH PROJECTS RELATED
TO THE DISSERTATION BY THE PHD CANDIDATE**

1. Dao Minh Hoang, Nguyen Thi Tuyet Mai, Nguyen Hoang Linh, Nguyen Binh Minh (2025), 'What drive young Vietnamese consumers to adopt Medical AI?', *Journal of Finance & Accounting Research*, No.03(34)-2025, Academy of Finance
2. Hoang Minh Dao, Linh Hoang Nguyen, Duong Dang Linh Dan, Nguyen Thi Tuyet Mai (2025), 'Determinants of consumer intention to adopt medical AI in an emerging economy: The role of self-concept and initial trust', *Telematics and Informatics Reports*, Volume 18, June 2025, 100213, Elsevier B.V.

REFERENCES

1. Agarwal, R. and Karahanna, E. (2000), 'Time Flies When You're Having Fun: Cognitive Absorption and Beliefs about Information Technology Usage', *MIS Quarterly*, 24(4), 665–694, retrieved on December 17, 2025, from [https://www.jstor.org/stable/3250951].
2. Agarwal, R. and Prasad, J. (1998), 'A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology', *Information Systems Research*, 9(2), 204–215, retrieved on May 6, 2025, from [https://pubsonline.informs.org/doi/10.1287/isre.9.2.204].
3. Ahmad, N. and Harun, A. (2023), 'Reasons for tourist intention to use e-bike sharing services; an application behavioral reasoning theory (BRT)', *Tourism Review*, 79(9), 1542–1559, retrieved on September 9, 2025, from [https://doi.org/10.1108/TR-03-2023-0165].
4. Ahmad, N. and Rasheed, H.M.W. (2024), 'SMEs and digital marketing: A perspective of behavioral reasoning theory', *Tourism and Hospitality Research*, 14673584241300600, retrieved on September 9, 2025, from [https://doi.org/10.1177/14673584241300600].
5. Ajzen, I. (1991), 'The theory of planned behavior', *Organizational Behavior and Human Decision Processes*, 50(2), 179–211, retrieved on April 11, 2025, from [https://www.sciencedirect.com/science/article/pii/074959789190020T].
6. Akingbola, A. et al. (2024), 'Artificial Intelligence and the Dehumanization of Patient Care', *Journal of Medicine, Surgery, and Public Health*, 3, 100138, retrieved on July 16, 2025, from [https://www.sciencedirect.com/science/article/pii/S2949916X24000914].
7. Albarracín, D. (2002), 'Cognition in persuasion: An analysis of information processing in response to persuasive communications', in *Advances in experimental social psychology*, Elsevier, 61–130.
8. Albarracín, D. et al. (2005), 'Attitudes: Introduction and scope', *The handbook of attitudes*, 2005, 3–19.

9. Albarracin, D. and Shavitt, S. (2018), 'Attitudes and Attitude Change', *Annual Review of Psychology*, 69(Volume 69, 2018), 299–327, retrieved on September 8, 2025, from [<https://www.annualreviews.org/content/journals/10.1146/annurev-psych-122216-011911>].
10. Albarracin, D. and Wyer Jr., R.S. (2001), 'Elaborative and Nonelaborative Processing of a Behavior-Related Communication', *Personality and Social Psychology Bulletin*, 27(6), 691–705, retrieved on September 18, 2025, from [<https://doi.org/10.1177/0146167201276005>].
11. Alexander, R.D. (1974), 'The Evolution of Social Behavior', *Annual Review of Ecology, Evolution, and Systematics*, 5, 325–383, retrieved on June 28, 2025, from [<https://www.annualreviews.org/content/journals/10.1146/annurev.es.05.110174.001545>].
12. Álvarez-Marín, A., Velázquez-Iturbide, J.Á. and Castillo-Vergara, M. (2023), 'The acceptance of augmented reality in engineering education: The role of technology optimism and technology innovativeness', *Interactive Learning Environments*, 31(6), 3409–3421, retrieved on August 21, 2025, from [<https://doi.org/10.1080/10494820.2021.1928710>].
13. Ashfaq, M. et al. (2021), 'You plant a virtual tree, we'll plant a real tree: Understanding users' adoption of the Ant Forest mobile gaming application from a behavioral reasoning theory perspective', *Journal of Cleaner Production*, 310, 127394, retrieved on September 9, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0959652621016139>].
14. Bagozzi, R.P. (2007), 'The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift.', *Journal of the Association for Information Systems*, 8(4), 3, retrieved on December 20, 2024, from [<http://aisel.aisnet.org/jais/vol8/iss4/3>].
15. Bagozzi, R.P., Bergami, M. and Leone, L. (2003), 'Hierarchical representation of motives in goal setting', *Journal of Applied Psychology*, 88(5), 915–943.
16. Bandura, A. (1989), 'Human agency in social cognitive theory', *American Psychologist*, 44(9), 1175–1184.

17. Barclay, D., Higgins, C. and Thompson, R. (1995), The partial least squares (PLS) approach to casual modeling: personal computer adoption ans use as an Illustration.
18. Becker, J.-M., Klein, K. and Wetzels, M. (2012), 'Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models', *Long Range Planning*, 45(5), 359–394, retrieved on July 12, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0024630112000611>].
19. Belanche, D., Casaló, L.V. and Flavián, C. (2021), 'Frontline robots in tourism and hospitality: service enhancement or cost reduction?', *Electronic Markets*, 31(3), 477–492, retrieved on July 15, 2025, from [<https://doi.org/10.1007/s12525-020-00432-5>].
20. Berente, N. et al. (2021), 'Managing Artificial Intelligence1', *Management Information Systems Quarterly*, 45(3), 1433–1450, retrieved on October 30, 2025, from [<https://doi.org/10.25300/MISQ/2021/16274>].
21. Bhattacharjee, A. and Hikmet, N. (2007), 'Physicians' resistance toward healthcare information technology: a theoretical model and empirical test', *European Journal of Information Systems*, 16(6), 725–737, retrieved on October 30, 2025, from [<https://doi.org/10.1057/palgrave.ejis.3000717>].
22. Bigman, Y.E. and Gray, K. (2018), 'People are averse to machines making moral decisions', *Cognition*, 181, 21–34, retrieved on August 30, 2024, from [<https://www.sciencedirect.com/science/article/pii/S0010027718302087>].
23. Blut, M. and Wang, C. (2020), 'Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage', *Journal of the Academy of Marketing Science*, 48(4), 649–669, retrieved on September 7, 2025, from [<https://doi.org/10.1007/s11747-019-00680-8>].
24. Boslaugh, S.E. (2016), *Anthropocentrism | Human-Centered Philosophy & Ethics | Britannica*, retrieved on March 10, 2024, from [<https://www.britannica.com/topic/anthropocentrism>].
25. Bostrom, N. (2014), *Superintelligence: paths, dangers, strategies*, First edition, Oxford University Press, Oxford.

26. Braun, V. and Clarke, V. (2006), 'Using thematic analysis in psychology', *Qualitative Research in Psychology*, 3(2), 77–101, retrieved on August 20, 2025, from [<https://doi.org/10.1191/1478088706qp063oa>].
27. BritCham Vietnam (2021), *Vietnam Health Supplements Report, Vietnam*, retrieved on November 30, 2025, from [<https://britchamvn.com/wp-content/uploads/2021/08/Vietnam-Health-Supplements-Report.pdf>].
28. Bui, T. et al. (2022), 'Effort–reward ratio, over-commitment and burnout: a cross-sectional study among Vietnamese healthcare professionals', *Cogent Psychology*, 9.
29. Çakal, H. et al. (2021), 'Intergroup contact and endorsement of social change motivations: The mediating role of intergroup trust, perspective-taking, and intergroup anxiety among three advantaged groups in Northern Cyprus, Romania, and Israel', *Group Processes & Intergroup Relations*, 24(1), 48–67, retrieved on June 28, 2025, from [<https://doi.org/10.1177/1368430219885163>].
30. Castelo, N., Bos, M.W. and Lehmann, D.R. (2019), 'Task-Dependent Algorithm Aversion', *Journal of Marketing Research*, 56(5), 809–825, retrieved on July 22, 2025, from [<https://doi.org/10.1177/0022243719851788>].
31. Cave, S., Coughlan, K. and Dihal, K. (2019), "'Scary Robots": Examining Public Responses to AI', in *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*. Association for Computing Machinery, New York, NY, USA, (AIES '19), 331–337, retrieved on July 10, 2025, from [<https://dl.acm.org/doi/10.1145/3306618.3314232>].
32. Chanh, H.Q. et al. (2023), 'Applying artificial intelligence and digital health technologies, Viet Nam', *Bulletin of the World Health Organization*, 101(7), 487–492, retrieved on October 13, 2023, from [<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10300774/>].
33. Chatterjee, S. et al. (2021), 'Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model', *Technological Forecasting and Social Change*, 170, 120880, retrieved on August 1, 2024, from [<https://www.sciencedirect.com/science/article/pii/S0040162521003127>].
34. Chatzidakis, A. and Lee, M.S.W. (2013), 'Anti-Consumption as the Study of Reasons against', *Journal of Macromarketing*, 33(3), 190–203, retrieved on September 18, 2025, from [<https://doi.org/10.1177/0276146712462892>].

35. Chong, A.Y.-L. (2013), 'A two-staged SEM-neural network approach for understanding and predicting the determinants of m-commerce adoption', *Expert Systems with Applications*, 40(4), 1240–1247, retrieved on August 21, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0957417412010287>].
36. Choudhary, S. et al. (2025), 'Assessing Factors Influencing Customers' Adoption of AI-Based Voice Assistants', *Journal of Computer Information Systems*, 65(5), 592–609, retrieved on September 17, 2025, from [<https://doi.org/10.1080/08874417.2024.2312858>].
37. Chuc, N.D. and Anh, D.T. (2023), 'Digital transformation in Vietnam', *Journal of Southeast Asian Economies*, 40(1), 127–144.
38. Chung, N., Han, H. and Joun, Y. (2015), 'Tourists' intention to visit a destination: The role of augmented reality (AR) application for a heritage site', *Computers in Human Behavior*, 50, 588–599, retrieved on August 21, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0747563215002101>].
39. Ciecierski-Holmes, T. et al. (2022), 'Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: A systematic scoping review', *npj Digital Medicine*, 5(1), 162, retrieved on September 7, 2025, from [<https://www.nature.com/articles/s41746-022-00700-y>].
40. Claudy, M.C., Garcia, R. and O'Driscoll, A. (2015), 'Consumer resistance to innovation—a behavioral reasoning perspective', *Journal of the Academy of Marketing Science*, 43(4), 528–544, retrieved on June 13, 2025, from [<https://doi.org/10.1007/s11747-014-0399-0>].
41. Claudy, M.C. and Peterson, M. (2014), 'Understanding the Underutilization of Urban Bicycle Commuting: A Behavioral Reasoning Perspective', *Journal of Public Policy & Marketing*, 33(2), 173–187, retrieved on June 16, 2025, from [<https://doi.org/10.1509/jppm.13.087>].
42. Claudy, M.C., Peterson, M. and O'Driscoll, A. (2013), 'Understanding the Attitude-Behavior Gap for Renewable Energy Systems Using Behavioral Reasoning Theory', *Journal of Macromarketing*, 33(4), 273–287, retrieved on July 16, 2025, from [<https://doi.org/10.1177/0276146713481605>].

43. Colby, C.L. and Parasuraman, A. (2001), *Techno-Ready Marketing: How and Why Customers Adopt Technology*, Simon and Schuster, New York, USA.
44. Cordina, J. et al. (2024), 'How AI in healthcare can improve consumer experiences', *McKinsey*, November, July 15, 2025, from [https://www.mckinsey.com/industries/healthcare/our-insights/harnessing-ai-to-reshape-consumer-experiences-in-healthcare?utm_source=chatgpt.com].
45. Creswell, J.W. and Plano Clark, V.L. (2018), *Designing and conducting mixed methods research*, Third edition, Sage, Los Angeles, Calif London New Delhi Singapore Washington DC Melbourne.
46. Cui, Y. (2025), 'What influences college students using AI for academic writing? - A quantitative analysis based on HISAM and TRI theory', *Computers and Education: Artificial Intelligence*, 8, 100391, retrieved on July 13, 2025, from [<https://www.sciencedirect.com/science/article/pii/S2666920X25000311>].
47. Cunneen, M., Mullins, M. and Murphy, F. (2019), 'Autonomous Vehicles and Embedded Artificial Intelligence: The Challenges of Framing Machine Driving Decisions', *Applied Artificial Intelligence*, 33(8), 706–731, retrieved on August 1, 2024, from [<https://doi.org/10.1080/08839514.2019.1600301>].
48. Danaher, J. (2022), 'Techno-optimism: An Analysis, an Evaluation and a Modest Defence', *Philosophy & Technology*, 35(2), 54, retrieved on July 12, 2025, from [<https://doi.org/10.1007/s13347-022-00550-2>].
49. Davenport, T. et al. (2020), 'How artificial intelligence will change the future of marketing', *Journal of the Academy of Marketing Science*, 48(1), 24–42, retrieved on July 23, 2025, from [<https://doi.org/10.1007/s11747-019-00696-0>].
50. Davenport, T. and Kalakota, R. (2019), 'The potential for artificial intelligence in healthcare', *Future Healthcare Journal*, 6(2), 94–98, retrieved on July 15, 2025, from [<https://www.sciencedirect.com/science/article/pii/S2514664524010592>].
51. Davenport, T.H. and Ronanki, R. (2018), 'Artificial intelligence for the real world', *Harvard Business Review*, 96(1), 108–116.
52. Davis, F.D. (1989), 'Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology', *MIS Quarterly*, 13(3), 319, retrieved on June 16, 2024, from [<https://www.jstor.org/stable/249008?origin=crossref>].

53. Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), 'User Acceptance of Computer Technology: A Comparison of Two Theoretical Models', *Management Science*, 35(8), 982–1003, retrieved on June 19, 2025, from [https://pubsonline.informs.org/doi/ 10.1287/mnsc.35.8.982].
54. Deng, Z., Mo, X. and Liu, S. (2014), 'Comparison of the middle-aged and older users' adoption of mobile health services in China', *International Journal of Medical Informatics*, 83(3), 210–224, retrieved on July 24, 2025, from [https://linkinghub.elsevier.com/retrieve/pii/S1386505613002499].
55. Diamantopoulos, A., Riefler, P. and Roth, K.P. (2008), 'Advancing formative measurement models', *Journal of Business Research*, 61(12), 1203–1218, retrieved on July 12, 2025, from [https://www.sciencedirect.com/science/article/pii/S0148296308000118].
56. Dietvorst, B.J., Simmons, J.P. and Massey, C. (2015), 'Algorithm aversion: People erroneously avoid algorithms after seeing them err', *Journal of Experimental Psychology: General*, 144(1), 114–126.
57. Do, T.T.T. et al. (2018), 'Receptiveness and preferences of health-related smartphone applications among Vietnamese youth and young adults', *BMC Public Health*, 18(1), 764, retrieved on November 30, 2025, from [https://doi.org/10.1186/s12889-018-5641-0].
58. Dwivedi, Y.K. et al. (2021), 'Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy', *International Journal of Information Management*, 57, 101994, retrieved on June 17, 2024, from [https://www.sciencedirect.com/science/article/pii/S026840121930917X].
59. Esmaeilzadeh, P. (2020), 'Use of AI-based tools for healthcare purposes: a survey study from consumers' perspectives', *BMC Medical Informatics and Decision Making*, 20(1), 170, retrieved on August 29, 2024, from [https://doi.org/10.1186/s12911-020-01191-1].
60. European Commission (2018), *Artificial Intelligence for Europe*, COM/2018/237 final, retrieved on July 23, 2025, from [https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=COM:2018:237:FIN].

61. Fagan, M., Kilmon, C. and Pandey, V. (2012), 'Exploring the adoption of a virtual reality simulation: The role of perceived ease of use, perceived usefulness and personal innovativeness', *Campus-Wide Information Systems*, 29(2), 117–127, retrieved on August 21, 2025, from [https://doi.org/10.1108/10650741211212368].
62. Fan, W. et al. (2020), 'Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS)', *Annals of Operations Research*, 294(1), 567–592, retrieved on July 21, 2025, from [https://link.springer.com/article/10.1007/s10479-018-2818-y].
63. Federspiel, F. et al. (2023), 'Threats by artificial intelligence to human health and human existence', *BMJ Global Health*, 8(5), retrieved on July 15, 2025, from [https://gh.bmj.com/content/8/5/e010435].
64. Ferrari, F., Paladino, M.P. and Jetten, J. (2016), 'Blurring Human–Machine Distinctions: Anthropomorphic Appearance in Social Robots as a Threat to Human Distinctiveness', *International Journal of Social Robotics*, 8(2), 287–302, retrieved on July 15, 2025, from [https://doi.org/10.1007/s12369-016-0338-y].
65. Fetzters, M.D., Curry, L.A. and Creswell, J.W. (2013), 'Achieving Integration in Mixed Methods Designs—Principles and Practices', *Health Services Research*, 48(6pt2), 2134–2156, retrieved on August 21, 2025, from [https://onlinelibrary.wiley.com/doi/abs/10.1111/1475-6773.12117].
66. Fiestas Lopez Guido, J.C. et al. (2025), 'The impact of master–servant relationships in human–robot collaboration on customer perceptions and behaviors in frontline retail encounters', *Journal of Service Management* [Preprint], retrieved on June 24, 2025, from [https://www.emerald.com/insight/content/doi/10.1108/JOSM-12-2023-0530/full/html].
67. Fishbein, M. and Ajzen, I. (1975), *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*, Addison-Wesley Publishing Company.
68. Fishbein, M. and Ajzen, I. (2005), 'Theory-based Behavior Change Interventions: Comments on Hobbis and Sutton', *Journal of Health Psychology*, 10(1), 27–31, retrieved on September 8, 2025, from [https://doi.org/10.1177/1359105305048552].

69. Fishbein, M. and Ajzen, I. (2010), *Predicting and changing behavior: The reasoned action approach*, Psychology Press, New York, NY, US, (Predicting and changing behavior: The reasoned action approach).
70. Fishbein, M. and Ajzen, I. (2011), *Predicting and Changing Behavior. 0 edn*, Psychology Press, retrieved on August 21, 2025, from [<https://www.taylorfrancis.com/books/9781136874734>].
71. Flanders Investment & Trade (2023), *Healthcare in Vietnam*, from [https://export.flandersinvestmentandtrade.com/sites/fit_domains/files/media/report/2023%2520Healthcare%2520in%2520Vietnam.pdf].
72. Flavián, C. et al. (2021), ‘Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness’, *Journal of Service Management*, 33(2), 293–320, retrieved on May 6, 2025, from [<https://www.emerald.com/insight/content/doi/10.1108/josm-10-2020-0378/full/html>].
73. Fornell, C. and Larcker, D.F. (1981), ‘Evaluating Structural Equation Models with Unobservable Variables and Measurement Error’, *Journal of Marketing Research*, 18(1), 39–50, retrieved on September 3, 2025, from [<https://doi.org/10.1177/002224378101800104>].
74. Fortuna, P. et al. (2022), ‘Barriers of Human and Nonhuman Agents’ Integration in Positive Hybrid Systems: The Relationship Between the Anthropocentrism, Artificial Intelligence Anxiety, and Attitudes Towards Humanoid Robots’, *Journal for Perspectives of Economic Political and Social Integration*, 28(2), 121–149, retrieved on March 4, 2024, from [<https://ojs.tnku.pl/index.php/jpepsi/article/view/17935>].
75. Fortuna, P. et al. (2024), ‘The relationship between anthropocentric beliefs and the moral status of a chimpanzee, humanoid robot, and cyborg person: The mediating role of the assignment of mind and soul’, *Current Psychology*, 43(14), 12664–12679, retrieved on August 21, 2025, from [<https://doi.org/10.1007/s12144-023-05313-6>].
76. Fortuna, P., Wróblewski, Z. and Gorbaniuk, O. (2023), ‘The structure and correlates of anthropocentrism as a psychological construct’, *Current Psychology: Research and Reviews*, 42(5), 3630–3642, retrieved on June 15, 2024, from [<https://www.proquest.com/docview/2789895034/abstract/D79081D2B0A04F78PQ/1>].

77. Frank, D.-A. et al. (2021), 'Drivers and social implications of Artificial Intelligence adoption in healthcare during the COVID-19 pandemic', *PLOS ONE*, 16(11), e0259928, retrieved on August 29, 2024, from [https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0259928].
78. Fritsch, S.J. et al. (2022), 'Attitudes and perception of artificial intelligence in healthcare: A cross-sectional survey among patients', *DIGITAL HEALTH*, 8, 20552076221116772, retrieved on September 16, 2025, from [https://doi.org/10.1177/20552076221116772].
79. Gaczek, P. et al. (2023), 'Overcoming Consumer Resistance to AI in General Health Care', *Journal of Interactive Marketing*, 58(2–3), 321–338, retrieved on August 28, 2024, from [http://journals.sagepub.com/doi/10.1177/10949968221151061].
80. Gagnon Thompson, S.C. and Barton, M.A. (1994), 'Ecocentric and anthropocentric attitudes toward the environment', *Journal of Environmental Psychology*, 14(2), 149–157, retrieved on May 6, 2025, from [https://www.sciencedirect.com/science/article/pii/S0272494405801689].
81. Gambino, A., Fox, J. and Ratan, R.A. (2020), 'Building a stronger CASA: Extending the computers are social actors paradigm', *Human-Machine Communication*, 1, 71–85, retrieved on September 9, 2025, from [https://search.informit.org/doi/abs/10.3316/INFORMIT.097034846749023].
82. Gefen, D., Karahanna, E. and Straub, D.W. (2003), 'Trust and TAM in Online Shopping: An Integrated Model', *MIS Quarterly*, 27(1), 51–90, retrieved on June 15, 2024, from [https://www.jstor.org/stable/30036519].
83. Geisser, S. (1975), 'The Predictive Sample Reuse Method with Applications', *Journal of the American Statistical Association*, 70(350), 320–328, retrieved on September 3, 2025, from [https://www.tandfonline.com/doi/abs/10.1080/01621459.1975.10479865].
84. Gigerenzer, G. and Goldstein, D.G. (1996), 'Reasoning the fast and frugal way: Models of bounded rationality', *Psychological Review*, 103(4), 650–669.
85. Gilly, M.C., Celsi, M.W. and Schau, H.J. (2012), 'It Don't Come Easy: Overcoming Obstacles to Technology Use Within a Resistant Consumer Group', *Journal of Consumer Affairs*, 46(1), 62–89, retrieved on September 14, 2025, from [https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1745-6606.2011.01218.x].

86. Glikson, E. and Woolley, A.W. (2020), 'Human Trust in Artificial Intelligence: Review of Empirical Research', *Academy of Management Annals*, 14(2), 627–660, retrieved on June 15, 2024, from [https://journals.aom.org/doi/10.5465/annals.2018.0057].
87. Glinskaya, E.E. et al. (2021), *Vietnam: Adapting to An Aging Society, Vietnam*, retrieved on July 23, 2025, from [https://documents1.worldbank.org/curated/en/544371632385243499/pdf/Vietnam-Adapting-to-an-Aging-Society.pdf].
88. Goertzel, B. and Pennachin, C. (eds) (2007), *Artificial general intelligence*, Springer, Berlin; New York, (Cognitive technologies).
89. Gollwitzer, P.M. (1999), 'Implementation intentions: Strong effects of simple plans', *American Psychologist*, 54(7), 493–503.
90. de Graaf, M.M.A., Allouch, S.B. and Klamer, T. (2015), 'Sharing a life with Harvey: Exploring the acceptance of and relationship-building with a social robot', *Computers in Human Behavior*, 43, 1–14, retrieved on July 15, 2025, from [https://www.sciencedirect.com/science/article/pii/S0747563214005536].
91. Granados Samayoa, J.A. and Albarracín, D. (2025), 'Understanding Belief-Behavior Correspondence: Beliefs and Belief-to-Behavior Inferences', *Psychological Inquiry*, 36(1), 1–22, retrieved on July 13, 2025, from [https://doi.org/10.1080/1047840X.2025.2482343].
92. Guest, G., Bunce, A. and Johnson, L. (2006), 'How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability', *Field Methods*, 18(1), 59–82, retrieved on August 20, 2025, from [https://doi.org/10.1177/1525822X05279903].
93. Gunaratne, S.A. (2009), 'Globalization: A Non-Western Perspective: The Bias of Social Science/Communication Oligopoly', *Communication, Culture and Critique*, 2(1), 60–82, retrieved on September 7, 2025, from [https://doi.org/10.1111/j.1753-9137.2008.01029.x].
94. Gupta, A. and Arora, N. (2017), 'Understanding determinants and barriers of mobile shopping adoption using behavioral reasoning theory', *Journal of Retailing and Consumer Services*, 36, 1–7, retrieved on July 15, 2025, from [https://www.sciencedirect.com/science/article/pii/S0969698916303502].

95. Haenlein, M. and Kaplan, A. (2019), 'A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence', *California Management Review*, 61(4), 5–14, retrieved on July 18, 2025, from [https://doi.org/10.1177/0008125619864925].
96. Haggadone, B.A., Banks, Jaime and and Koban, K. (2021), 'Of robots and robotkind: Extending intergroup contact theory to social machines', *Communication Research Reports*, 38(3), 161–171, retrieved on June 24, 2025, from [https://doi.org/10.1080/08824096.2021.1909551].
97. Hair, J.F. (2014), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, SAGE.
98. Hair, J.F. et al. (2017), *A primer on partial least squares structural equation modeling (PLS-SEM)*, Second edition, SAGE, Los Angeles London New Delhi Singapore Washington DC Melbourne.
99. Hair, J.F. et al. (2021), *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*, Springer International Publishing, Cham, (Classroom Companion: Business), retrieved on December 1, 2024, from [https://link.springer.com/10.1007/978-3-030-80519-7].
100. Hair, J.F. et al. (2022), *A primer on partial least squares structural equation modeling (PLS-SEM)*, Third edition, SAGE, Los Angeles.
101. Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), 'PLS-SEM: Indeed a Silver Bullet', *Journal of Marketing Theory and Practice*, 19(2), 139–152, retrieved on September 2, 2025, from [https://doi.org/10.2753/MTP1069-6679190202].
102. Hajiheydari, N., Delgosha, M.S. and Saheb, T. (2025), 'AI in medical diagnosis: A contextualised study of patient motivations and concerns', *Social Science & Medicine*, 371, 117850, retrieved on September 16, 2025, from [https://www.sciencedirect.com/science/article/pii/S0277953625001790].
103. Hashimoto, D.A. et al. (2018), 'Artificial Intelligence in Surgery: Promises and Perils', *Annals of Surgery*, 268(1), 70–76.
104. Haslam, N. (2006), 'Dehumanization: An Integrative Review', *Personality and Social Psychology Review*, 10(3), 252–264, retrieved on July 15, 2025, from [https://doi.org/10.1207/s15327957pspr1003_4].

105. Havlík, V. (2019), 'The naturalness of artificial intelligence from the evolutionary perspective', *AI & SOCIETY*, 34(4), 889–898, retrieved on September 7, 2025, from [<https://doi.org/10.1007/s00146-018-0829-5>].
106. Hayward, T. (1997), 'Anthropocentrism: A Misunderstood Problem', *Environmental Values*, 6(1), 49–63, retrieved on September 6, 2025, from [<https://www.jstor.org/stable/30301484>].
107. He, J. et al. (2019), 'The practical implementation of artificial intelligence technologies in medicine', *Nature medicine*, 25(1), 30–36.
108. Heidenreich, S. and Handrich, M. (2015), 'Adoption of technology-based services: The role of customers' willingness to co-create', *Journal of Service Management*, 26(1), 44–71, retrieved on December 13, 2023, from [<https://doi.org/10.1108/JOSM-03-2014-0079>].
109. Henseler, J., Hubona, G. and Ray, P.A. (2016), 'Using PLS path modeling in new technology research: updated guidelines', *Industrial Management & Data Systems*, 116(1), 2–20, retrieved on September 3, 2025, from [<https://doi.org/10.1108/IMDS-09-2015-0382>].
110. Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), 'A new criterion for assessing discriminant validity in variance-based structural equation modeling', *Journal of the Academy of Marketing Science*, 43(1), 115–135, retrieved on April 11, 2025, from [<https://doi.org/10.1007/s11747-014-0403-8>].
111. Hildebrand, C. and Bergner, A. (2021), 'Conversational robo advisors as surrogates of trust: Onboarding experience, firm perception, and consumer financial decision making', *Journal of the Academy of Marketing Science*, 49(4), 659–676, retrieved on July 22, 2025, from [<https://doi.org/10.1007/s11747-020-00753-z>].
112. Ho, Manh-Tung et al. (2023), 'Understanding the acceptance of emotional artificial intelligence in Japanese healthcare system: A cross-sectional survey of clinic visitors' attitude', *Technology in Society*, 72, 102166, retrieved on August 29, 2024, from [<https://www.sciencedirect.com/science/article/pii/S0160791X22003074>].
113. Ho, M.-T. et al. (2022), 'Rethinking technological acceptance in the age of emotional AI: Surveying Gen Z (Zoomer) attitudes toward non-conscious data collection', *Technology in Society*, 70, 102011, retrieved on September 14, 2024, from [<https://www.sciencedirect.com/science/article/pii/S0160791X2200152X>].

114. Holden, R.J. and Karsh, B.-T. (2010), 'The Technology Acceptance Model: Its past and its future in health care', *Journal of Biomedical Informatics*, 43(1), 159–172, retrieved on July 24, 2025, from [<https://linkinghub.elsevier.com/retrieve/pii/S1532046409000963>].
115. Hu, L. and Bentler, P.M. (1999), 'Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives', *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55, retrieved on September 3, 2025, from [<https://doi.org/10.1080/10705519909540118>].
116. Huang, H.-L. et al. (2021), 'The Effects of Perceived Identity Threat and Realistic Threat on the Negative Attitudes and Usage Intentions Toward Hotel Service Robots: The Moderating Effect of the Robot's Anthropomorphism', *International Journal of Social Robotics*, 13(7), 1599–1611, retrieved on May 6, 2025, from [<https://doi.org/10.1007/s12369-021-00752-2>].
117. Huang, M.-H. and Rust, R.T. (2018), 'Artificial Intelligence in Service', *Journal of Service Research*, 21(2), 155–172, retrieved on July 22, 2025, from [<https://doi.org/10.1177/1094670517752459>].
118. Huang, M.-H. and Rust, R.T. (2021a), 'A strategic framework for artificial intelligence in marketing', *Journal of the Academy of Marketing Science*, 49(1), 30–50, retrieved on July 18, 2024, from [<http://link.springer.com/10.1007/s11747-020-00749-9>].
119. Huang, M.-H. and Rust, R.T. (2021b), 'Engaged to a Robot? The Role of AI in Service', *Journal of Service Research*, 24(1), 30–41, retrieved on July 15, 2025, from [<https://doi.org/10.1177/1094670520902266>].
120. Huang, S., LeBlanc, J. and Choi, H.C. (2016), 'How do Chinese tourists differ from Caucasian tourists? An empirical study from the perspective of tourists' self-concept', *International Journal of Tourism Sciences*, 16(4), 222–237, retrieved on December 1, 2025, from [<https://doi.org/10.1080/15980634.2016.1257868>].
121. Huang, Y. and Qian, L. (2021), 'Understanding the potential adoption of autonomous vehicles in China: The perspective of behavioral reasoning theory', *Psychology & Marketing*, 38(4), 669–690, retrieved on July 21, 2025, from [<https://onlinelibrary.wiley.com/doi/abs/10.1002/mar.21465>].

122. Huo, W. et al. (2024), 'Speciesism and Preference of Human–Artificial Intelligence Interaction: A Study on Medical Artificial Intelligence', *International Journal of Human–Computer Interaction*, 40(11), 2925–2937, retrieved on September 9, 2025, from [<https://doi.org/10.1080/10447318.2023.2176985>].
123. Hwang, J. and Good, L. (2014), 'Intelligent sensor-based services success: the role of consumer characteristics and information', *European Journal of Marketing*, 48(3–4), 406–431, retrieved on September 14, 2025, from [<https://doi.org/10.1108/EJM-11-2011-0689>].
124. IBM (2023), *Understanding the different types of artificial intelligence*, retrieved on July 18, 2025, from [<https://www.ibm.com/think/topics/artificial-intelligence-types>].
125. Ikari, S. et al. (2023), 'Religion-Related Values Differently Influence Moral Attitude for Robots in the United States and Japan', *Journal of Cross-Cultural Psychology*, 54(6–7), 742–759, retrieved on September 26, 2024, from [<https://doi.org/10.1177/00220221231193369>].
126. Jain, V., Wadhwani, K. and Eastman, J.K. (2024), 'Artificial intelligence consumer behavior: A hybrid review and research agenda', *Journal of Consumer Behaviour*, 23(2), 676–697, retrieved on September 5, 2024, from [<https://onlinelibrary.wiley.com/doi/10.1002/cb.2233>].
127. Jamal, A. (2004), 'Retail Banking and Customer Behaviour: A Study of Self Concept, Satisfaction and Technology Usage', *The International Review of Retail, Distribution and Consumer Research*, 14(3), 357–379, retrieved on July 16, 2025, from [<https://doi.org/10.1080/09593960410001678381>].
128. Jan, I.U., Ji, S. and Kim, C. (2023), 'What (de) motivates customers to use AI-powered conversational agents for shopping? The extended behavioral reasoning perspective', *Journal of Retailing and Consumer Services*, 75, 103440, retrieved on July 16, 2025, from [<https://www.sciencedirect.com/science/article/pii/S096969892300187X>].
129. Jarvenpaa, S.L., Tractinsky, N. and Vitale, M. (2000), 'Consumer trust in an Internet store', *Information Technology and Management*, 1(1–2), 45–71, retrieved on July 24, 2025, from [<https://link.springer.com/10.1023/A:1019104520776>].

130. Javalgi, R. (Raj) G. et al. (2013), 'Antecedents of Taiwan Chinese Consumers' Purchase Intentions Toward U.S.- and Japanese-Made Household Appliances', *Journal of Global Marketing*, 26(4), 203–223, retrieved on June 26, 2025, from [https://doi.org/10.1080/08911762.2013.814820].
131. Jeong, S.C. and Choi, B.-J. (2022), 'Moderating Effects of Consumers' Personal Innovativeness on the Adoption and Purchase Intention of Wearable Devices', *SAGE Open*, 12(4), 21582440221134798, retrieved on September 17, 2025, from [https://doi.org/10.1177/21582440221134798].
132. Jetten, J., Spears, R. and Manstead, A.S.R. (1996), 'Intergroup norms and intergroup discrimination: Distinctive self-categorization and social identity effects', *Journal of Personality and Social Psychology*, 71(6), 1222–1233.
133. Kaplan, A. and Haenlein, M. (2020), 'Rulers of the world, unite! The challenges and opportunities of artificial intelligence', *Business Horizons*, 63(1), 37–50, retrieved on July 15, 2025, from [https://www.sciencedirect.com/science/article/pii/S0007681319301260].
134. Kappmeier, M., Guenoun, B. and Fahey, K.H. (2021), 'Conceptualizing trust between groups: An empirical validation of the five-dimensional intergroup trust model', *Peace and Conflict: Journal of Peace Psychology*, 27(1), 90–95.
135. Katz, D. (1960), 'THE FUNCTIONAL APPROACH TO THE STUDY OF ATTITUDES', *Public Opinion Quarterly*, 24(2), 163–204, retrieved on September 18, 2025, from [https://doi.org/10.1086/266945].
136. Kaushik, A. et al. (2025), 'Challenges and Opportunities for Data Sharing Related to Artificial Intelligence Tools in Health Care in Low- and Middle-Income Countries: Systematic Review and Case Study From Thailand', *Journal of Medical Internet Research*, 27(1), e58338, retrieved on September 7, 2025, from [https://www.jmir.org/2025/1/e58338].
137. Kelly, S., Kaye, S.-A. and Oviedo-Trespalacios, O. (2023), 'What factors contribute to the acceptance of artificial intelligence? A systematic review', *Telematics and Informatics*, 77, 101925.
138. Khanijahani, A. et al. (2022), 'Organizational, professional, and patient characteristics associated with artificial intelligence adoption in healthcare: A systematic review', *Health Policy and Technology*, 11(1), 100602, retrieved on October 12, 2023, from [https://www.sciencedirect.com/science/article/pii/S2211883722000089].

139. Khechine, H., Lakhal, S. and Ndjambou, P. (2016), 'A meta-analysis of the UTAUT model: Eleven years later', *Canadian Journal of Administrative Sciences / Revue Canadienne des Sciences de l'Administration*, 33(2), 138–152, retrieved on September 8, 2025, from [https://onlinelibrary.wiley.com/doi/abs/10.1002/cjas.1381].
140. Kim, H.M. and Ryu, K. (2021), 'Examining Image Congruence and Its Consequences in the Context of Robotic Coffee Shops', *Sustainability*, 13(20), 11413, retrieved on July 24, 2025, from [https://www.mdpi.com/2071-1050/13/20/11413].
141. King, W.R. and He, J. (2006), 'A meta-analysis of the technology acceptance model', *Information & Management*, 43(6), 740–755, retrieved on September 8, 2025, from [https://www.sciencedirect.com/science/article/pii/S0378720606000528].
142. Kock, N. (2015), 'Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach', *International Journal of e-Collaboration (IJeC)*, 11(4), 1–10, retrieved on February 8, 2025, from [https://www.igi-global.com/article/common-method-bias-in-pls-sem/www.igi-global.com/article/common-method-bias-in-pls-sem/132843].
143. Kock, N. and Hadaya, P. (2018), 'Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods', *Information Systems Journal*, 28(1), 227–261, retrieved on September 3, 2025, from [https://onlinelibrary.wiley.com/doi/abs/10.1111/isj.12131].
144. Kopnina, H. et al. (2018), 'Anthropocentrism: More than Just a Misunderstood Problem', *Journal of Agricultural and Environmental Ethics*, 31(1), 109–127, retrieved on September 7, 2025, from [https://doi.org/10.1007/s10806-018-9711-1].
145. Kortenkamp, K.V. and Moore, C.F. (2001), 'Ecocentrism and anthropocentrism: moral reasoning about ecological commons dilemmas', *Journal of Environmental Psychology*, 21(3), 261–272, retrieved on July 5, 2025, from [https://www.sciencedirect.com/science/article/pii/S0272494401902051].
146. KPMG and Oxford University Clinical Research Unit (2020), *Digital Health in Vietnam, Vietnam*, retrieved on September 7, 2025, from [https://assets.kpmg.com/content/dam/kpmg/vn/pdf/publication/2021/1/Digital-Health-in-Vietnam-Market-Intelligence-Report.pdf].
147. Krueger, R.A. and Casey, M.A. (2015), *Focus groups: A practical guide for applied research. 5th edition*, SAGE, Los Angeles London New Delhi Singapore Washington DC.

148. Kumar, A., Kumar, D.V.S. and Megha, R.U. (2025), 'Customer adoption of artificial intelligence in healthcare: An empirical investigation based on multiple samples', *Health Marketing Quarterly*, 42(2), 204–228, retrieved on December 1, 2025, from [<https://doi.org/10.1080/07359683.2025.2504811>].
149. Kumar, P., Vrontis, D. and Pallonetto, F. (2024), 'Cognitive engagement with AI-enabled technologies and value creation in healthcare', *Journal of Consumer Behaviour*, 23(2), 389–404, retrieved on September 5, 2024, from [<https://onlinelibrary.wiley.com/doi/abs/10.1002/cb.2196>].
150. Kunda, Z. (1990), 'The case for motivated reasoning', *Psychological Bulletin*, 108(3), 480–498.
151. Kunz, W.H. and Wirtz, J. (2023), 'AI in Customer Service: A Service Revolution in the Making', in J.N. Sheth et al. (eds) *Artificial Intelligence in Customer Service: The Next Frontier for Personalized Engagement*. Springer International Publishing, Cham, 15–32, retrieved on August 22, 2025, from [https://doi.org/10.1007/978-3-031-33898-4_2].
152. Kurniawan, M.H. et al. (2024), 'A systematic review of artificial intelligence-powered (AI-powered) chatbot intervention for managing chronic illness', *Annals of Medicine*, 56(1), 2302980, retrieved on July 23, 2025, from [<https://doi.org/10.1080/07853890.2024.2302980>].
153. Lalicic, L. and Weismayer, C. (2021), 'Consumers' reasons and perceived value co-creation of using artificial intelligence-enabled travel service agents', *Journal of Business Research*, 129, 891–901, retrieved on July 21, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0148296320307487>].
154. Lambert, S.D. and Loiselle, C.G. (2008), 'Combining individual interviews and focus groups to enhance data richness', *Journal of Advanced Nursing*, 62(2), 228–237, retrieved on August 21, 2025, from [<https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2648.2007.04559.x>].
155. Le, N. (2024), *Vietnam aims for 15 doctors per 10,000 people by 2025*, *VnExpress International*, retrieved on July 23, 2025, from [<https://e.vnexpress.net/news/news/vietnam-aims-for-15-doctors-per-10-000-people-by-2025-4716651.html>].

156. Le, N. (2025), *Vietnam's birth rate among lowest in Southeast Asia*, *VnExpress International – Latest news, business, travel and analysis from Vietnam*, retrieved on September 7, 2025, from [<https://e.vnexpress.net/news/news/vietnam-s-birth-rate-among-lowest-in-southeast-asia-4852684.html>].
157. Lee, J.-C., Chen, L. and Zhang, H. (2023), 'Exploring the adoption decisions of mobile health service users: a behavioral reasoning theory perspective', *Industrial Management & Data Systems*, 123(8), 2241–2266, retrieved on July 16, 2025, from [<https://www.emerald.com/insight/content/doi/10.1108/imds-11-2022-0682/full/html>].
158. Lee, J.D. and See, K.A. (2004), 'Trust in Automation: Designing for Appropriate Reliance', *Human Factors*, 46(1), 50–80, retrieved on June 19, 2025, from [<https://journals.sagepub.com/action/showAbstract>].
159. Lee, Y., Kozar, K.A. and Larsen, K.R.T. (2003), 'The Technology Acceptance Model: Past, Present, and Future', *Communications of the Association for Information Systems*, 12, retrieved on September 8, 2025, from [<https://aisel.aisnet.org/cais/vol12/iss1/50>].
160. Leung, L. and Cheung, M. (2025), 'The effects of technology readiness, risks, and benefits on smart home technology adoption: Extending the Theory of Planned Behavior model', *Media Asia*, 52(1), 80–101, retrieved on December 2, 2025, from [<https://www.tandfonline.com/doi/full/10.1080/01296612.2024.2330771>].
161. Li, W. and Wang, J. (2024), 'Determinants of artificial intelligence-assisted diagnostic system adoption intention: A behavioral reasoning theory perspective', *Technology in Society*, 78, 102643, retrieved on September 8, 2024, from [<https://www.sciencedirect.com/science/article/pii/S0160791X2400191X>].
162. Li, X., Hess, T.J. and Valacich, J.S. (2008), 'Why do we trust new technology? A study of initial trust formation with organizational information systems', *The Journal of Strategic Information Systems*, 17(1), 39–71, retrieved on September 14, 2024, from [<https://www.sciencedirect.com/science/article/pii/S0963868708000036>].

163. Liao, S. et al. (2024), 'Why not work with anthropomorphic collaborative robots? The mediation effect of perceived intelligence and the moderation effect of self-efficacy', *Human Factors and Ergonomics in Manufacturing & Service Industries*, 34(3), 241–260, retrieved on June 24, 2025, from [<https://onlinelibrary.wiley.com/doi/abs/10.1002/hfm.21024>].
164. Liljander, V. et al. (2006), 'Technology readiness and the evaluation and adoption of self-service technologies', *Journal of Retailing and Consumer Services*, 13(3), 177–191, retrieved on September 18, 2025, from [<https://www.sciencedirect.com/science/article/pii/S096969890500055X>].
165. Lillemäe, E., Talves, K. and Wagner, W. (2025), 'Public perception of military AI in the context of techno-optimistic society', *AI & SOCIETY*, 40(2), 929–943, retrieved on September 14, 2025, from [<https://doi.org/10.1007/s00146-023-01785-z>].
166. Lin, J.-S.C. and Hsieh, P.-L. (2007), 'The influence of technology readiness on satisfaction and behavioral intentions toward self-service technologies', *Computers in Human Behavior*, 23(3), 1597–1615, retrieved on July 12, 2025, from [<https://www.sciencedirect.com/science/article/pii/S074756320500052X>].
167. Logg, J.M., Minson, J.A. and Moore, D.A. (2019), 'Algorithm appreciation: People prefer algorithmic to human judgment', *Organizational Behavior and Human Decision Processes*, 151, 90–103, retrieved on July 22, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0749597818303388>].
168. Longoni, C., Bonezzi, A. and Morewedge, C.K. (2019), 'Resistance to Medical Artificial Intelligence', *Journal of Consumer Research*, 46(4), 629–650, retrieved on October 12, 2023, from [<https://doi.org/10.1093/jcr/ucz013>].
169. Lu, J., Yao, J.E. and Yu, C.-S. (2005), 'Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology', *The Journal of Strategic Information Systems*, 14(3), 245–268, retrieved on December 17, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0963868705000399>].
170. Lu, L. and Yang, K.-S. (2006), 'Emergence and composition of the traditional-modern bicultural self of people in contemporary Taiwanese societies', *Asian Journal of Social Psychology*, 9(3), 167–175, retrieved on April 22, 2025, from [<https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-839X.2006.00195.x>].

171. Ma, X. and Huo, Y. (2023), 'Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework', *Technology in Society*, 75, 102362, retrieved on July 22, 2025, from [https://www.sciencedirect.com/science/article/pii/S0160791X23001677].
172. Maher, J.P. et al. (2017), 'Momentary assessment of physical activity intention-behavior coupling in adults', *Translational Behavioral Medicine*, 7(4), 709–718, retrieved on August 21, 2025, from [https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5684065/].
173. Mak, K.-K. and Pichika, M.R. (2019), 'Artificial intelligence in drug development: present status and future prospects', *Drug Discovery Today*, 24(3), 773–780, retrieved on July 23, 2025, from [https://www.sciencedirect.com/science/article/pii/S1359644618300916].
174. Mariani, M.M., Perez-Vega, R. and Wirtz, J. (2022), 'AI in marketing, consumer research and psychology: A systematic literature review and research agenda', *Psychology & Marketing*, 39(4), 755–776, retrieved on August 1, 2024, from [https://onlinelibrary.wiley.com/doi/abs/10.1002/mar.21619].
175. Markus, H. and Wurf, E. (1987), 'The dynamic self-concept: A social psychological perspective', *Annual Review of Psychology*, 38, 299–337.
176. Markus, H.R. and Kitayama, S. (1998), 'Culture and the Self: Implications for Cognition, Emotion, and Motivation', in *College Student Development and Academic Life*, Routledge.
177. McCarthy, J. (2007), *What is artificial intelligence*.
178. McCracken, G. (1988), *The Long Interview*, SAGE Publications, Inc., 2455 Teller Road, Newbury Park California 91320 United States of America, retrieved on August 21, 2025, from [https://methods.sagepub.com/book/the-long-interview].
179. McKinsey (2021), *The new faces of the Vietnamese consumer*, retrieved on November 30, 2025, from [https://www.mckinsey.com/featured-insights/future-of-asia/the-new-faces-of-the-vietnamese-consumer#/].
180. Mcknight, D.H. et al. (2011), 'Trust in a specific technology: An investigation of its components and measures', *ACM Trans. Manage. Inf. Syst.*, 2(2), 12:1-12:25, retrieved on September 14, 2024, from [https://dl.acm.org/doi/10.1145/1985347.1985353].

181. McKnight, D.H., Cummings, L.L. and Chervany, N.L. (1998), 'Initial Trust Formation in New Organizational Relationships', *The Academy of Management Review*, 23(3), 473–490, retrieved on June 19, 2025, from [https://www.jstor.org/stable/259290].
182. Mick, D.G. and Fournier, S. (1998), 'Paradoxes of Technology: Consumer Cognizance, Emotions, and Coping Strategies', *Journal of Consumer Research*, 25(2), 123–143, retrieved on July 15, 2025, from [https://doi.org/10.1086/209531].
183. Millet, K. et al. (2023), 'Defending humankind: Anthropocentric bias in the appreciation of AI art', *Computers in Human Behavior*, 143, 107707, retrieved on September 11, 2025, from [https://www.sciencedirect.com/science/article/pii/S0747563223000584].
184. Ministry of Health (2019), 'Decision No.5349/QĐ-BYT Approving plan for deployment of electronic health records', *Ministry of Health*, retrieved on July 23, 2025, from [https://thuvienhadat.vn/van-ban-phap-luat-viet-nam/decision-5349-qd-byt-2019-approving-plan-for-deployment-of-electronic-health-records-428693.html].
185. Ministry of Health of Vietnam (2019), 'Decision 4888/QĐ-BYT 2019 introducing the scheme for application and development of smart healthcare information technology for the 2019–2025 period', *Ministry of Health, Hanoi*, retrieved on February 6, 2026, from [https://thuvienphapluat.vn/van-ban/EN/Cong-nghe-thong-tin/Decision-4888-QĐ-BYT-2019-the-scheme-for-application-of-smart-healthcare-information-technology/428330/tieng-anh.aspx].
186. Ministry of Science and Technology (2024), *Digital infrastructure strategy approved*, *Digital Portal of Ministry of Science and Technology*, retrieved on September 7, 2025, from [https://english.mic.gov.vn/digital-infrastructure-strategy-approved-197241010150835947.htm].
187. Minsky, M. (1988), *Semantic information processing*, 6. pr, MIT Pr, Cambridge, Mass.
188. Mirbabaie, M. et al. (2022), 'The rise of artificial intelligence – understanding the AI identity threat at the workplace', *Electronic Markets*, 32(1), 73–99, retrieved on July 15, 2025, from [https://doi.org/10.1007/s12525-021-00496-x].

189. Modliński, A. and Trump, R.K. (2025), 'The impact of speciesism on customers' acceptance of service automation', *Journal of Service Theory and Practice*, 35(2), 245–262, retrieved on September 11, 2025, from [<https://doi.org/10.1108/JSTP-06-2024-0200>].
190. Morgan, D.L. (1996), 'Focus Groups', *Annual Review of Sociology*, 22(Volume 22, 1996), 129–152, retrieved on August 21, 2025, from [<https://www.annualreviews.org/content/journals/10.1146/annurev.soc.22.1.129>].
191. Mou, Y., Gong, Y. and Ding, Z. (2024), 'Complement or substitute? A study of the impact of artificial intelligence on consumers' resistance', *Marketing Intelligence & Planning*, 42(4), 647–665, retrieved on June 28, 2025, from [<https://www.emerald.com/insight/content/doi/10.1108/mip-04-2023-0187/full/html>].
192. Nadarzynski, T. et al. (2019), 'Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: A mixed-methods study', *DIGITAL HEALTH*, 5, 2055207619871808, retrieved on October 12, 2023, from [<https://doi.org/10.1177/2055207619871808>].
193. Nass, C.I. et al. (1995), 'Anthropocentrism and computers', *Behaviour & Information Technology*, 14(4), 229–238, retrieved on June 15, 2024, from [<https://doi.org/10.1080/01449299508914636>].
194. Nguyen, H. (2024), VN targets 15 doctors per 10,000 people by 2025, VietNamNet News, retrieved on September 7, 2025, from [https://vietnamnet.vn/en/vn-targets-15-doctors-per-10-000-people-by-2025-2254601.html?utm_source=chatgpt.com].
195. Nguyen, H.L. et al. (2022), 'Demand for Mobile Health in Developing Countries During COVID-19: Vietnamese's Perspectives from Different Age Groups and Health Conditions', *Patient preference and adherence*, 16, 265–284, retrieved on November 30, 2025, from [<https://pmc.ncbi.nlm.nih.gov/articles/PMC8819166/>].
196. Nguyen, H.T.T. et al. (2018), 'Burnout Study of Clinical Nurses in Vietnam: Development of Job Burnout Model Based on Leiter and Maslach's Theory', *Asian Nursing Research*, 12(1), 42–49, retrieved on July 23, 2025, from [<https://www.sciencedirect.com/science/article/pii/S1976131717302797>].

197. Nguyen, M.T.T., Smith, K. and Cao, J.R. (2009), 'Measurement of Modern and Traditional Self-Concepts in Asian Transitional Economies', *Journal of Asia-Pacific Business*, 10(3), 201–220, retrieved on September 16, 2024, from [https://doi.org/10.1080/10599230903094745].
198. Nguyen, T.K.C. and Vu, H.N. (2023), 'Investigating the customer trust in artificial intelligence: The role of anthropomorphism, empathy response, and interaction', *CAAI Transactions on Intelligence Technology*, 8(1), 260–273, retrieved on September 14, 2024, from [https://onlinelibrary.wiley.com/doi/abs/10.1049/cit2.12133].
199. Nguyen, T.T.M. et al. (2019), 'Antecedents of Purchase Intention toward Organic Food in an Asian Emerging Market: A Study of Urban Vietnamese Consumers', *Food*, 11(17), 4773, retrieved on April 13, 2025, from [https://www.mdpi.com/2071-1050/11/17/4773].
200. Oliveira, T. et al. (2014), 'Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM', *International Journal of Information Management*, 34(5), 689–703, retrieved on April 11, 2025, from [https://www.sciencedirect.com/science/article/pii/S0268401214000668].
201. Othman, A.K., Hamzah, M.I. and Abu Hassan, L.F. (2020), 'Modeling the contingent role of technological optimism on customer satisfaction with self-service technologies: A case of cash-recycling ATMs', *Journal of Enterprise Information Management*, 33(3), 559–578, retrieved on September 14, 2025, from [https://doi.org/10.1108/JEIM-09-2019-0295].
202. Oyserman, D., Smith, G.C. and Elmore, K. (2014), 'Identity-Based Motivation: Implications for Health and Health Disparities', *Journal of Social Issues*, 70(2), 206–225, retrieved on September 8, 2025, from [https://onlinelibrary.wiley.com/doi/abs/10.1111/josi.12056].
203. Palaniappan, K., Lin, E.Y.T. and Vogel, S. (2024), 'Global Regulatory Frameworks for the Use of Artificial Intelligence (AI) in the Healthcare Services Sector', *Healthcare*, 12(5), 562, retrieved on October 30, 2025, from [https://pmc.ncbi.nlm.nih.gov/articles/PMC10930608/].

204. Parasuraman, A. (2000), 'Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies', *Journal of Service Research*, 2(4), 307–320, retrieved on May 6, 2025, from [https://doi.org/10.1177/109467050024001].
205. Park, S.S., Tung, C.D. and Lee, H. (2021), 'The adoption of AI service robots: A comparison between credence and experience service settings', *Psychology & Marketing*, 38(4), 691–703, retrieved on July 24, 2025, from [https://onlinelibrary.wiley.com/doi/10.1002/mar.21468].
206. Patton, M.Q. (2014), *Qualitative research & evaluation methods: Integrating theory and practice*, Sage publications.
207. Pennington, N. and Hastie, R. (1988), 'Explanation-based decision making: Effects of memory structure on judgment', *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14(3), 521–533.
208. Pennington, N. and Hastie, R. (1992), 'Explaining the evidence: Tests of the Story Model for juror decision making', *Journal of Personality and Social Psychology*, 62(2), 189–206.
209. Pennington, N. and Hastie, R. (1993), 'Reasoning in explanation-based decision making', *Cognition*, 49(1), 123–163, retrieved on June 19, 2025, from [https://www.sciencedirect.com/science/article/pii/001002779390038W].
210. Perrone, M. (2025), *As AI nurses reshape hospital care, human nurses push back*, AP News, 17 March, July 16, 2025, from [https://apnews.com/article/artificial-intelligence-ai-nurses-hospitals-health-care-3e41c0a2768a3b4c5e002270cc2abe23].
211. Pham, T. (2025), 'Ethical and legal considerations in healthcare AI: innovation and policy for safe and fair use', *Royal Society Open Science*, 12(5), 241873, retrieved on December 2, 2025, from [https://pmc.ncbi.nlm.nih.gov/articles/PMC12076083/].
212. Pillai, R. et al. (2023), 'Adoption of artificial intelligence (AI) based employee experience (EEX) chatbots', *Information Technology & People*, 37(1), 449–478, retrieved on July 15, 2025, from [https://www.emerald.com/insight/content/doi/10.1108/itp-04-2022-0287/full/html].
213. Plsek, P.E. and Greenhalgh, T. (2001), 'The challenge of complexity in health care', *BMJ*, 323(7313), 625–628, retrieved on July 23, 2025, from [https://www.bmj.com/content/323/7313/625].

214. Podsakoff, P.M. et al. (2003), 'Common method biases in behavioral research: A critical review of the literature and recommended remedies', *Journal of Applied Psychology*, 88(5), 879–903.
215. Politburo of the Communist Party of Vietnam (2019), 'Resolution No. 52-NQ/TW of the Politburo on a number of guidelines and policies to actively participate in the Fourth Industrial Revolution', *Central Committee of the Communist Party of Vietnam, Hanoi*, retrieved on February 6, 2026, from [<https://english.luatvietnam.vn/resolution-no-52-nq-tw-of-the-central-committee-on-a-number-of-guidelines-and-policies-to-actively-participate-in-the-fourth-industrial-revolution-177121-doc1.html>].
216. Prakash, A.V. and Das, S. (2021), 'Medical practitioner's adoption of intelligent clinical diagnostic decision support systems: A mixed-methods study', *Information & Management*, 58(7), 103524, retrieved on September 11, 2024, from [<https://www.sciencedirect.com/science/article/pii/S0378720621000987>].
217. Promberger, M. and Baron, J. (2006), 'Do patients trust computers?', *Journal of Behavioral Decision Making*, 19(5), 455–468.
218. Quan, N.K. and Taylor-Robinson, A.W. (2022), 'Vietnam's Evolving Healthcare System: Notable Successes and Significant Challenges', *Cureus*, 15(6), e40414, retrieved on July 23, 2025, from [<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10348075/>].
219. Richey, R.G., Daugherty, P.J. and Roath, A.S. (2007), 'Firm technological readiness and complementarity: Capabilities impacting logistics service competency and performance', *Journal of Business Logistics*, 28(1), 195–228, retrieved on August 21, 2025, from [<http://dx.doi.org/10.1002/j.2158-1592.2007.tb00237.x>].
220. Riek, B.M., Mania, E.W. and Gaertner, S.L. (2006), 'Intergroup Threat and Outgroup Attitudes: A Meta-Analytic Review', *Personality and Social Psychology Review*, 10(4), 336–353, retrieved on June 28, 2025, from [https://doi.org/10.1207/s15327957pspr1004_4].
221. Roe, R.M., Bussemeyer, J.R. and Townsend, J.T. (2001), 'Multialternative decision field theory: A dynamic connectionst model of decision making', *Psychological Review*, 108(2), 370.

222. Rogers, E.M. (2003), *Diffusion of innovations*, Fifth edition, Free Press, New York London Toronto Sydney.
223. Roppelt, J.S., Kanbach, D.K. and Kraus, S. (2024), 'Artificial intelligence in healthcare institutions: A systematic literature review on influencing factors', *Technology in Society*, 76, 102443, retrieved on July 15, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0160791X23002488>].
224. Russell, S.J. and Norvig, P. (2016), *Artificial intelligence: A modern approach*, Pearson.
225. Ryan, J. and Casidy, R. (2018), 'The role of brand reputation in organic food consumption: A behavioral reasoning perspective', *Journal of Retailing and Consumer Services*, 41, 239–247, retrieved on June 14, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0969698917304502>].
226. Sahu, A.K., Padhy, R.K. and Dhir, A. (2020), 'Envisioning the Future of Behavioral Decision-Making: A Systematic Literature Review of Behavioral Reasoning Theory', *Australasian Marketing Journal*, 28(4), 145–159, retrieved on July 3, 2025, from [<https://doi.org/10.1016/j.ausmj.2020.05.001>].
227. Sarstedt, M. et al. (2019), 'How to specify, estimate, and validate higher-order constructs in PLS-SEM', *Australasian Marketing Journal (AMJ)*, 27(3), 197–211, retrieved on July 12, 2025, from [<https://www.sciencedirect.com/science/article/pii/S1441358219301223>].
228. Schepers, J. and Wetzels, M. (2007), 'A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects', *Information & Management*, 44(1), 90–103, retrieved on September 8, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0378720606001170>].
229. Schmitt, B. (2020), 'Speciesism: an obstacle to AI and robot adoption', *Marketing Letters*, 31(1), 3–6, retrieved on September 9, 2025, from [<https://doi.org/10.1007/s11002-019-09499-3>].
230. Shaik, T. et al. (2023), 'Remote patient monitoring using artificial intelligence: Current state, applications, and challenges', *WIREs Data Mining and Knowledge Discovery*, 13(2), e1485, retrieved on July 23, 2025, from [<https://onlinelibrary.wiley.com/doi/abs/10.1002/widm.1485>].

231. Shamszare, H. and Choudhury, A. (2023), 'Clinicians' Perceptions of Artificial Intelligence: Focus on Workload, Risk, Trust, Clinical Decision Making, and Clinical Integration', *Healthcare*, 11(16), 2308, retrieved on July 15, 2025, from [https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10454426/].
232. Shi, J. et al. (2025), 'Empowering individuals to adopt artificial intelligence for health information seeking: A latent profile analysis among users in Hong Kong', *Social Science & Medicine*, 375, 118059, retrieved on September 9, 2025, from [https://www.sciencedirect.com/science/article/pii/S0277953625003892].
233. Silverman, D. (ed.) (2009), *Qualitative research: theory, method and practice*. 2. ed., reprinted, SAGE Publ, Los Angeles, Calif.
234. Sirgy, M.J. (1985), 'Using self-congruity and ideal congruity to predict purchase motivation', *Journal of Business Research*, 13(3), 195–206, retrieved on February 5, 2025, from [https://www.sciencedirect.com/science/article/pii/0148296385900268].
235. Sivathanu, B. (2018), 'Adoption of internet of things (IOT) based wearables for healthcare of older adults – a behavioural reasoning theory (BRT) approach', *Journal of Enabling Technologies*, 12(4), 169–185, retrieved on December 10, 2025, from [https://doi.org/10.1108/JET-12-2017-0048].
236. Snyder, C.R. (1980), *Uniqueness: The Human Pursuit of Difference*, 1st ed, Springer, Boston.
237. Söllner, M., Hoffmann, A. and Leimeister, J.M. (2016), 'Why different trust relationships matter for information systems users', *European Journal of Information Systems*, 25(3), 274–287, retrieved on August 22, 2025, from [https://doi.org/10.1057/ejis.2015.17].
238. Son, M. and Han, K. (2011), 'Beyond the technology adoption: Technology readiness effects on post-adoption behavior', *Journal of Management Information Systems*, 27(4), 1178–1182, retrieved on September 14, 2025, from [https://www.sciencedirect.com/science/article/pii/S0148296311002062].
239. Stephan, W.G., Ybarra, O. and Bachman, G. (1999), 'Prejudice Toward Immigrants', *Journal of Applied Social Psychology*, 29(11), 2221–2237, retrieved on June 26, 2025, from [https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1559-1816.1999.tb00107.x].

240. Stone, M. (1974), 'Cross-Validatory Choice and Assessment of Statistical Predictions', *Journal of the Royal Statistical Society: Series B (Methodological)*, 36(2), 111–133, retrieved on September 3, 2025, from [https://doi.org/10.1111/j.2517-6161.1974.tb00994.x].
241. Tao, D. et al. (2020), 'A systematic review and meta-analysis of user acceptance of consumer-oriented health information technologies', i104, 106147, retrieved on July 24, 2025, from [https://linkinghub.elsevier.com/retrieve/pii/S0747563219303516].
242. Taylor, S. and Todd, P.A. (1995), 'Understanding Information Technology Usage: A Test of Competing Models', *Information Systems Research*, 6(2), 144–176, retrieved on August 21, 2025, from [https://pubsonline.informs.org/doi/10.1287/isre.6.2.144].
243. Tetlock, P.E., Skitka, L. and Boettger, R. (1989), 'Social and cognitive strategies for coping with accountability: Conformity, complexity, and bolstering', *Journal of Personality and Social Psychology*, 57(4), 632–640.
244. The Prime Minister (2020), 'Decision No. 749/QĐ-TTg 2020 National Digital Transformation Program to 2025 with orientation toward 2030', *Government of Vietnam*, retrieved on July 23, 2025, from [https://english.luatvietnam.vn/decision-no-749-qd-ttg-on-approving-the-national-digital-transformation-program-until-2025-with-a-vision-184241-doc1.html].
245. The Prime Minister (2022), 'Decision No. 06/QĐ-TTg 2022 Approving the Scheme on developing the application of data on population, identification, electronic authentication data for national digital transformation in the 2022-2025 period, with a vision toward 2030', *Government of Vietnam, Hanoi*, retrieved on February 6, 2026, from [https://english.luatvietnam.vn/decision-no-06-qd-ttg-dated-january-06-2022-of-the-prime-minister-approving-the-scheme-on-developing-the-application-of-data-on-population-identifi-215370-doc1.html].
246. Thu, T.N.D., Nguyen, Q.K. and Taylor-Robinson, A.W. (2023), 'Healthcare in Vietnam: Harnessing Artificial Intelligence and Robotics to Improve Patient Care Outcomes', *Cureus*, 15(9).
247. Tian, K.T., Bearden, W.O. and Hunter, G.L. (2001), 'Consumers' Need for Uniqueness: Scale Development and Validation', *Journal of Consumer Research*, 28(1), 50–66, retrieved on July 20, 2025, from [https://doi.org/10.1086/321947].

248. Topol, E.J. (2019), *Deep medicine: how artificial intelligence can make healthcare human again*, First edition, Basic Books, New York, NY.
249. Tran, A.Q. et al. (2021), ‘Determinants of Intention to Use Artificial Intelligence-Based Diagnosis Support System Among Prospective Physicians’, *Frontiers in Public Health*, 9, retrieved on September 11, 2023, from [<https://www.frontiersin.org/articles/10.3389/fpubh.2021.755644>].
250. Tran, B.X. et al. (2018), ‘What Drives Young Vietnamese to Use Mobile Health Innovations? Implications for Health Communication and Behavioral Interventions’, *JMIR mHealth and uHealth*, 6(11), e194.
251. Tran, D. et al. (2023), ‘Status of Digital Health Technology Adoption in Five Vietnamese hospitals: Cross-sectional Assessment (Preprint)’, *JMIR Formative Research*, 9.
252. Tran, D.M. et al. (2022), ‘Digital Health Policy and Programs for Hospital Care in Vietnam: Scoping Review’, *Journal of Medical Internet Research*, 24(2), e32392, retrieved on September 7, 2025, from [<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8867296/>].
253. Trang, T.T.N., Thang, P.C. and Vo, T.A. (2025), ‘Moderating the AI Revolution: Perceived threat and generative AI implementation in Vietnamese hospitals’, *Computers in Human Behavior Reports*, 19, 100774, retrieved on August 20, 2025, from [<https://www.sciencedirect.com/science/article/pii/S2451958825001897>].
254. Tsikriktsis, N. (2004), ‘A Technology Readiness-Based Taxonomy of Customers: A Replication and Extension’, *Journal of Service Research*, 7(1), 42–52, retrieved on July 12, 2025, from [<https://doi.org/10.1177/1094670504266132>].
255. UNDP (2025), *Artificial Intelligence Landscape Assessment (AILA): Shaping AI to be an empowering force for people and planet, Vietnam*, retrieved on November 30, 2025, from [<https://www.undp.org/vietnam/publications/artificial-intelligence-landscape-assessment-aila-shaping-ai-be-empowering-force-people-and-planet>].
256. United Nations, Department of Economic and Social Affairs, Population Division (2024), *World Population Prospects, World Population Prospects 2024*, retrieved on November 30, 2025, from [<https://population.un.org/wpp/>].
257. Venkatesh, V. et al. (2003), ‘User Acceptance of Information Technology: Toward a Unified View’, *MIS Quarterly*, 27(3), 425–478, retrieved on July 21, 2025, from [<https://www.jstor.org/stable/30036540>].

258. Venkatesh, V. and Bala, H. (2008), 'Technology Acceptance Model 3 and a Research Agenda on Interventions', *Decision Sciences*, 39(2), 273–315, retrieved on September 8, 2025, from [<https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-5915.2008.00192.x>].
259. Venkatesh, V. and Davis, F.D. (2000), 'A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies', *Management Science*, 46(2), 186–204, retrieved on September 8, 2025, from [<https://pubsonline.informs.org/doi/abs/10.1287/mnsc.46.2.186.11926>].
260. Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012), 'Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology', *MIS Quarterly*, 36(1), 157–178, retrieved on June 16, 2024, from [<https://www.jstor.org/stable/41410412>].
261. Verma, S., Gupta, A. and Kashive, N. (2025), 'Exploring the Elderly's Resistance Toward mHealth Apps: The Role of Distrust, Technology Optimism, and Health Consciousness', *Services Marketing Quarterly*, 0(0), 1–37, retrieved on September 14, 2025, from [<https://doi.org/10.1080/15332969.2025.2503084>].
262. VietNamNet (2024), *Nvidia's Vietnam expansion: New AI hubs, VinBrain acquisition, and more*, *VietNamNet News*, retrieved on December 17, 2025, from [<https://vietnamnet.vn/en/nvidia-s-vietnam-expansion-new-ai-hubs-vinbrain-acquisition-and-more-2350158.html>].
263. VTV Online (2024), *Nền tảng AI của Việt Nam được triển khai ở 182 bệnh viện trên toàn cầu*. *Hanoi*, retrieved on February 5, 2026, from [<https://vtv.vn/cong-nghe/nen-tang-ai-cua-viet-nam-duoc-trien-khai-o-182-benh-vien-tren-toan-cau-20240612162618316.htm>].
264. Vu, K. and Fenton, S. (2024), *Nvidia to build AI research, data centres in Vietnam with gov*, *Reuters*, retrieved on July 23, 2025, from [<https://www.reuters.com/technology/nvidia-signs-ai-cooperation-agreement-with-vietnamese-government-2024-12-05/>].
265. Vu, K. and Nguyen, T. (2024), 'Exploring the contributors to the digital economy: Insights from Vietnam with comparisons to Thailand', *Telecommunications Policy*, 48(1), 102664.

266. Vuong, Q.-H. et al. (2019), 'Artificial Intelligence vs. Natural Stupidity: Evaluating AI Readiness for the Vietnamese Medical Information System', *Journal of Clinical Medicine*, 8(2), 168, retrieved on August 24, 2023, from [https://www.mdpi.com/2077-0383/8/2/168].
267. Wagner, M. and Westaby, J.D. (2020), 'Changing Pay Systems in Organizations: Using Behavioral Reasoning Theory to Understand Employee Support for Pay-for-Performance (or Not)', *The Journal of Applied Behavioral Science*, 56(3), 301–321, retrieved on September 9, 2025, from [https://journals.sagepub.com/doi/10.1177/0021886319896411].
268. von Walter, B., Kremmel, D. and Jäger, B. (2022), 'The impact of lay beliefs about AI on adoption of algorithmic advice', *Marketing Letters*, 33(1), 143–155, retrieved on July 22, 2025, from [https://doi.org/10.1007/s11002-021-09589-1].
269. Weger, U. and Herbig, K. (2021), 'The Self in the Periphery', *Review of General Psychology*, 25(1), 73–84, retrieved on September 7, 2025, from [https://doi.org/10.1177/1089268020954372].
270. Wei, X. et al. (2024), 'A meta-analysis of technology acceptance in healthcare from the consumer's perspective', *Health Marketing Quarterly*, 41(2), 192–213, retrieved on July 24, 2025, from [https://www.tandfonline.com/doi/full/10.1080/07359683.2024.2316425].
271. Westaby, J.D. (2005), 'Behavioral reasoning theory: Identifying new linkages underlying intentions and behavior', *Organizational Behavior and Human Decision Processes*, 98(2), 97–120, retrieved on June 13, 2025, from [https://www.sciencedirect.com/science/article/pii/S074959780500107X].
272. Westaby, J.D. and Fishbein, M. (1996), 'Factors Underlying Behavioral Choice: Testing a New Reasons Theory Approach', *Journal of Applied Social Psychology*, 26(15), 1307–1323, retrieved on June 19, 2025, from [https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1559-1816.1996.tb00072.x].
273. Westaby, J.D., Probst, T.M. and Lee, B.C. (2010), 'Leadership decision-making: A behavioral reasoning theory analysis', *The Leadership Quarterly*, 21(3), 481–495.
274. Westaby, J.D., Rosemarino, N.M. and Elliot, A.J. (2025), 'How Behavioral Reasoning May Further Explain the Belief-to-Behavior Connection: Exploring the Role of Primary Reasons, Counter Reasons, and Comparative Reasoning Facets', *Psychological Inquiry*, 36(1), 67–74, retrieved on July 4, 2025, from [https://doi.org/10.1080/1047840X.2025.2482353].

275. Wibowo, M.F. et al. (2025), 'Insights Into the Current and Future State of AI Adoption Within Health Systems in Southeast Asia: Cross-Sectional Qualitative Study', *Journal of Medical Internet Research*, 27(1), e71591, retrieved on September 16, 2025, from [<https://www.jmir.org/2025/1/e71591>].
276. Witte, K. (1992), 'Putting the fear back into fear appeals: The extended parallel process model', *Communication Monographs*, 59(4), 329–349, retrieved on June 26, 2025, from [<https://doi.org/10.1080/03637759209376276>].
277. Wong, K.K.-K. (2013), 'Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS', *Marketing bulletin*, 24(1), 1–32.
278. World Bank (2024), *Tổng Quan về Việt Nam*, *World Bank*, retrieved on September 7, 2025, from [<https://www.worldbank.org/vi/country/vietnam/overview>].
279. World Health Organization (2021), *Ethics and Governance of Artificial Intelligence for Health: WHO Guidance*, 1st ed, World Health Organization, Geneva.
280. World Health Organization (2022), *Medical doctors (per 10 000 population)*, *The Global Health Observatory - World Health Organization*, retrieved on September 7, 2025, from [[https://www.who.int/data/gho/data/indicators/indicator-details/GHO/medical-doctors-\(per-10-000-population\)](https://www.who.int/data/gho/data/indicators/indicator-details/GHO/medical-doctors-(per-10-000-population))].
281. World Health Organization (2024), *Global spending on health: coping with the pandemic*, World Health Organization.
282. World Health Organization (2025), *WHO warns of slowing global health gains in new statistics report*, retrieved on September 7, 2025, from [<https://www.who.int/news/item/15-05-2025-who-warns-of-slowing-global-health-gains-in-new-statistics-report>].
283. Wu, S.-I. and Chan, H.-J. (2011), 'Perceived service quality and self-concept influences on consumer attitude and purchase process: A comparison between physical and internet channels', *Total Quality Management & Business Excellence*, 22(1), 43–62, retrieved on July 16, 2025, from [<https://doi.org/10.1080/14783363.2010.529645>].
284. Yang, X. et al. (2025), 'Technological optimism surpasses fear of missing out: A multigroup analysis of presumed media influence on generative AI technology adoption across varying levels of technological optimism', *Computers in Human Behavior*, 162, 108466, retrieved on September 14, 2025, from [<https://www.sciencedirect.com/science/article/pii/S0747563224003340>].

285. Yang, Y., Ngai, E.W.T. and Wang, L. (2024), 'Resistance to artificial intelligence in health care: Literature review, conceptual framework, and research agenda', *Information & Management*, 61(4), 103961, retrieved on September 8, 2024, from [<https://www.sciencedirect.com/science/article/pii/S0378720624000430>].
286. Ye, T. et al. (2019), 'Psychosocial Factors Affecting Artificial Intelligence Adoption in Health Care in China: Cross-Sectional Study', *Journal of Medical Internet Research*, 21(10), e14316, retrieved on September 7, 2023, from [<http://www.jmir.org/2019/10/e14316/>].
287. Yi, M.Y., Fiedler, K.D. and Park, J.S. (2006), 'Understanding the Role of Individual Innovativeness in the Acceptance of IT-Based Innovations: Comparative Analyses of Models and Measures*', *Decision Sciences*, 37(3), 393–426, retrieved on June 19, 2025, from [<https://onlinelibrary.wiley.com/doi/10.1111/j.1540-5414.2006.00132.x>].
288. Young, A.T. et al. (2021), 'Patient and general public attitudes towards clinical artificial intelligence: A mixed methods systematic review', *The Lancet Digital Health*, 3(9), e599–e611, retrieved on September 7, 2025, from [https://www.thelancet.com/journals/landig/article/PIIS2589-7500%2821%2900132-1/fulltext?utm_source=chatgpt.com].
289. Zeng, D., Cao, Z. and Neill, D.B. (2021), 'Chapter 22 - Artificial intelligence-enabled public health surveillance—from local detection to global epidemic monitoring and control', in L. Xing, M.L. Giger, and J.K. Min (eds) *Artificial Intelligence in Medicine. Academic Press*, 437–453, retrieved on July 23, 2025, from [<https://www.sciencedirect.com/science/article/pii/B9780128212592000223>].
290. Zhang, B. and Dafoe, A. (2019), 'Artificial Intelligence: American Attitudes and Trends', *Social Science Research Network, Rochester, NY*, retrieved on June 19, 2025, from [<https://papers.ssrn.com/abstract=3312874>].
291. Zhang, H., Bai, X. and Ma, Z. (2022), 'Consumer reactions to AI design: Exploring consumer willingness to pay for AI-designed products', *Psychology & Marketing*, 39(11), 2171–2183, retrieved on August 22, 2025, from [<https://onlinelibrary.wiley.com/doi/abs/10.1002/mar.21721>].

292. Zhang, J. and Shavitt, S. (2003), 'Cultural Values in Advertisements to the Chinese X-Generation—Promoting Modernity and Individualism', *Journal of Advertising*, 32(1), 23–33, retrieved on June 19, 2025, from [<https://doi.org/10.1080/00913367.2003.10639047>].
293. Zhang, M. et al. (2017), 'Technical attributes, health attribute, consumer attributes and their roles in adoption intention of healthcare wearable technology', *International Journal of Medical Informatics*, 108, 97–109, retrieved on September 17, 2025, from [<https://www.sciencedirect.com/science/article/pii/S1386505617303568>].
294. Zhao, N. et al. (2019), 'The impact of traditionality/modernity on identification- and calculus-based trust', *International Journal of Psychology*, 54(2), 237–246, retrieved on December 20, 2024, from [<https://onlinelibrary.wiley.com/doi/abs/10.1002/ijop.12445>].
295. Złotowski, J., Yogeewaran, K. and Bartneck, C. (2017), 'Can we control it? Autonomous robots threaten human identity, uniqueness, safety, and resources', *International Journal of Human-Computer Studies*, 100, 48–54, retrieved on July 15, 2025, from [<https://www.sciencedirect.com/science/article/pii/S1071581916301768>].
296. Zuhair, V. et al. (2024), 'Exploring the Impact of Artificial Intelligence on Global Health and Enhancing Healthcare in Developing Nations', *Journal of Primary Care & Community Health*, 15, 21501319241245847, retrieved on September 16, 2025, from [<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC11010755/>].

APPENDICES

Appendix 1: Interview guide for the semi-structured interview

Topic: Determinants of intention to use artificial intelligence in healthcare: an empirical study in Vietnam

1. Record the participant's name, assign a coded identifier, note the interview time, and confirm the participant's informed consent to take part in the interview.
2. Before starting the interview, introduce yourself and thank the participant for their time and participation.
3. Introduce the study, its objectives, and the concept of artificial intelligence in healthcare, including several illustrative examples of AI applications in healthcare; emphasize the voluntary nature of participation and the participant's right to answer or decline to answer any question or to stop the interview at any time; and emphasize the confidentiality and anonymity of all information provided.
4. Request permission to audio-record the interview; if permission is not granted, take written notes instead.
5. Inform the participant of the expected duration of the interview.
6. Ask for permission to begin the interview and to proceed with audio recording and note-taking.

Section A: Study Information

Objective 1: To explore the current state of artificial intelligence adoption in healthcare in Vietnam.

Objective 2: To explore consumers' perceptions, beliefs, and factors influencing their intention to adopt artificial intelligence in healthcare.

Section B: Interview Questions

Target informants: Doctors

Objective 1: To explore the current state of artificial intelligence adoption in healthcare in Vietnam

- Could you briefly introduce your current professional role and responsibilities?
- Have you had any direct or indirect experience with AI applications in healthcare? If so, could you describe one or more specific examples and share your impressions or experiences with them?

- How do you assess the current application of AI in healthcare? From the perspective of a medical professional, could you share your views, expectations, or concerns regarding the implementation of AI in clinical practice?
- How do you evaluate the current level of AI adoption in the healthcare sector in Vietnam?
- Based on your observations, in which types of healthcare facilities are AI applications mainly being implemented (e.g., public vs. private hospitals, central-level vs. provincial-level institutions), and at which stages of the care process (e.g., screening, diagnosis, or treatment)?
- In your opinion, what specific benefits and potential risks may arise from the application of AI in healthcare?
- In your view, what advantages does the adoption of AI in healthcare currently bring in Vietnam, and what difficulties or challenges does it face?

Objective 2: To explore consumers' perceptions, beliefs, and factors influencing their intention to adopt AI in healthcare from the perspective of key stakeholders

- Do you believe that the role of physicians in the healthcare system should always remain central, even when AI can support or replace certain tasks? Why or why not?
- In your opinion, should AI primarily serve as a decision-support tool for physicians, or in certain situations be able to provide independent recommendations without direct human supervision? How does this view affect the physician–patient relationship?
- Based on your interactions with patients, how do you perceive patients' attitudes and reactions toward healthcare services that involve AI?
- In your opinion, do patients feel comfortable with AI participating in or replacing certain aspects of their healthcare process? Why do you think so?

Target informants: Policymakers

Objective 1: To explore the current state of artificial intelligence adoption in healthcare in Vietnam

- Could you briefly introduce your current position and professional responsibilities?
- From the perspective of a health policymaker, how do you assess the role and potential of AI in the current healthcare system?

- In your view, what benefits could the application of AI in healthcare bring to the healthcare system and to patients, and what risks or challenges does it pose that need to be managed at the policy level?
- How would you characterize the current situation and level of implementation of AI-based healthcare applications in Vietnam's healthcare sector?
- According to your assessment, in which types of healthcare institutions are AI applications currently being implemented (e.g., public vs. private hospitals, central-level vs. provincial-level facilities), and at which stages of the healthcare process (e.g., screening, diagnosis, or treatment)?
- From a policy perspective, what do you consider to be the main facilitating factors and barriers to the implementation of AI in healthcare in Vietnam? In addition, how do you evaluate the existing legal and policy frameworks governing the use of AI in healthcare?

Objective 2: To explore consumers' perceptions, beliefs, and factors influencing their intention to adopt AI in healthcare from the perspective of key stakeholders

- Do you believe that the role of physicians in the healthcare system should always remain central, even when AI can support or replace certain tasks? Why or why not?
- In your opinion, should AI in healthcare primarily function as a decision-support tool for physicians, or in some cases be allowed to make independent decisions without human supervision? Does this have any implications for the physician–patient relationship? Does it pose any potential risks to patients?

Target informants: Medical AI developer/ distributor

Objective 1: To explore the current state of artificial intelligence adoption in healthcare in Vietnam

- Could you briefly introduce your current role and professional responsibilities?
- From your perspective as a leader in a healthcare technology company, how do you assess the current application of AI in the healthcare sector?
- In your opinion, what core benefits does the adoption of AI in healthcare offer, and what key risks or challenges does it pose for service users and other stakeholders?

- How would you characterize the current state and level of AI implementation in medical examination and treatment in Vietnam?
- Based on your experience, in which types of healthcare facilities are AI-based solutions mainly being implemented (e.g., public vs. private hospitals, central-level vs. provincial-level institutions), and at which stages of the healthcare process (e.g., screening, diagnosis, or treatment)?
- How do you evaluate the facilitators and barriers to the implementation and scaling up of healthcare AI solutions in Vietnam, particularly from the consumer perspective?

Objective 2: To explore consumers' perceptions, beliefs, and factors influencing their intention to adopt AI in healthcare from the perspective of key stakeholders

- Based on your observations, what specific factors influence Vietnamese consumers' intention to use AI-based healthcare services?
- Do you believe that the role of physicians will change as AI becomes capable of supporting or replacing certain medical tasks? Why or why not?
- In your view, should AI in healthcare primarily serve as a decision-support tool for physicians, or in some cases be able to make independent decisions without direct physician supervision? How might this affect the physician–patient relationship?
- If you were a consumer, would you feel comfortable with AI being involved in your medical examination or treatment, for example in complex or life-critical decisions? Why or why not?
- Do you believe that physicians possess unique qualities that cannot be replaced by machines or technology? Why or why not?

Target Informants: Consumers

Objective 1: To explore the current state of artificial intelligence adoption in healthcare in Vietnam

- Could you briefly introduce your current occupation or work situation?
- When you hear about the use of AI in healthcare, what thoughts or feelings usually come to your mind?
- In your opinion, what benefits could the use of AI in medical examination and treatment bring to patients, and what risks or concerns do you have?

- Based on your knowledge or personal experience, are AI applications in healthcare currently common in Vietnam? In which types of healthcare facilities do you usually hear about or observe AI being used (e.g., public vs. private hospitals, central-level vs. provincial-level hospitals)? At which stages of the care process is AI most often applied, such as screening, diagnosis, or treatment monitoring?
- As a healthcare service consumer, what advantages and difficulties do you perceive in the current application of AI in healthcare in Vietnam?

Objective 2: To explore consumers' perceptions, beliefs, and factors influencing their intention to adopt AI in healthcare from the perspective of key stakeholders

- Would you be willing to use AI-based healthcare services when seeking medical care? Why or why not?
- In your view, does the role of physicians change as AI is increasingly used to support or replace certain tasks in medical care? Why?
- Do you think AI in healthcare should primarily support physicians, or in some cases be able to make independent decisions without physician supervision? Why?
- Would you feel comfortable with AI being involved in your medical examination or treatment, for example in complex or life-critical decisions? Why?
- Do you believe that physicians possess unique qualities that cannot be replaced by machines or technology? If so, what are those qualities?
- Do you think there are aspects of healthcare that physicians will always perform better than technology, regardless of technological advancements? If so, what aspects are they?
- When faced with conflicting recommendations from a physician and an AI system, whom would you trust more? Why?

Appendix 2: Focus group guide

Topic: Determinants of intention to use artificial intelligence in healthcare: an empirical study in Vietnam

Objective: To explore consumers' perceptions, beliefs, and the *reasons for* and *reasons against* adopting artificial intelligence in healthcare from the consumer perspective.

A. Initial Awareness and Familiarity

Main questions

- Have you ever heard of or learned about artificial intelligence (AI) in the healthcare sector?
- In your opinion, how familiar are consumers, especially young people, with AI in healthcare today?

Moderator probes (if needed)

- Where did you hear about AI in healthcare (e.g., media, hospitals, social networks, personal experience)?
- Can you give an example of an AI application you have heard about?

B. General Evaluations of AI in Healthcare

- In your opinion, what benefits can AI bring to healthcare services compared with physicians?
- What are your thoughts and feelings about the use of AI in healthcare?

Moderator probes (if needed)

- Do these thoughts feel more positive or negative overall?
- What experiences or information shaped these feelings?

C. Reasons for adopting AI in healthcare

- In which specific situations would you feel comfortable using AI? Why?
- How do you evaluate the diagnostic accuracy of AI compared with physicians?
- In your own healthcare experience, to what extent would you like AI to be involved?

Moderator probes (if needed)

- Would this apply to screening, diagnosis, treatment support, or follow-up care?
- Does your comfort depend on the severity of the illness or the complexity of the decision?

D. Reasons for not adopting medical AI

- In which specific situations would you feel uncomfortable using AI? Why?

- What do you think about the possibility of AI making errors during the diagnostic process?
- Do you have any concerns or apprehensions about using AI in healthcare? Why?

E. Trust Formation and Decision Logic

- What information would you need in order to trust healthcare services provided by AI?
- If you had the opportunity to experience healthcare services that apply AI, do you think you would feel satisfied with and trust such services?

F. The role of physicians

- Do you think the role of human physicians in healthcare services will change with the emergence of AI in healthcare? If so, why?
 - Would you be willing to accept AI directly participating in medical examinations or supporting the treatment process? Why?
 - Do you think AI can replace human physicians in certain roles? Why?
- Moderator probes (if needed)
- Which aspects of healthcare should always involve human physicians?
 - Are there roles where AI could fully replace humans, or should it always remain supportive?

Appendix 3: Survey questionnaire

PHIẾU CÂU HỎI

Số phiếu:

Khảo sát này hướng tới tìm hiểu các nhân tố ảnh hưởng tới ý định của người tiêu dùng chấp nhận sử dụng hệ thống hỗ trợ quyết định y khoa với sự hỗ trợ của AI khi tham gia khám chữa bệnh tại các cơ sở y tế. Những ý kiến của Anh/ Chị góp phần tạo nên sự thành công của đề tài. Các thông tin cá nhân sẽ được giữ bí mật.

Khảo sát dự kiến mất 7-10 phút để hoàn thành, mong anh/chị kiên nhẫn và đọc kỹ câu hỏi khi trả lời.

Định nghĩa và minh họa về hệ thống được cung cấp bên dưới để giúp anh/ chị hiểu được rõ hơn.

Xin chân thành cảm ơn đóng góp của Anh/ Chị!

Các định nghĩa liên quan

Trí tuệ nhân tạo (AI): việc sử dụng các hệ thống máy tính để mô phỏng những năng lực vốn có của con người, như thực hiện các công việc thể chất hoặc cơ học, tư duy và cảm nhận.

Hệ thống hỗ trợ quyết định y khoa có AI: là các ứng dụng máy tính được thiết kế để giúp các bác sĩ lâm sàng đưa ra quyết định chẩn đoán và điều trị... Trong các hệ thống do AI điều khiển, máy học và các kỹ thuật AI khác được sử dụng để xử lý lượng lớn dữ liệu lâm sàng, xác định các mô hình và cung cấp thông tin chi tiết hỗ trợ việc ra quyết định cụ thể cho từng bệnh nhân.

Minh họa 1: Hệ thống AI hỗ trợ chẩn đoán tổn thương trong nội soi

Trong quá trình nội soi, bác sĩ theo dõi màn hình có tích hợp AI. Hệ thống sẽ tự động khoanh vùng các vùng nghi ngờ tổn thương và đưa ra đề xuất nhằm hỗ trợ bác sĩ trong quá trình chẩn đoán.



Minh họa 2: Hệ thống hỗ trợ quyết định y khoa có AI trong chẩn đoán và điều trị ung thư

IBM Watson for Oncology là một hệ thống trí tuệ nhân tạo được phát triển để hỗ trợ bác sĩ trong việc chẩn đoán và điều trị ung thư. Dựa trên dữ liệu y khoa khổng lồ và hướng dẫn điều trị từ các chuyên gia, hệ thống đưa ra các phương án điều trị được cá nhân hóa cho từng bệnh nhân. Công cụ này giúp rút ngắn thời gian ra quyết định và nâng cao độ chính xác trong lâm sàng.



Minh họa 3: Hệ thống hỗ trợ quyết định y khoa có AI trong Chẩn đoán hình ảnh

DrAid là nền tảng trí tuệ nhân tạo do VinBrain phát triển nhằm hỗ trợ bác sĩ trong chẩn đoán hình ảnh y khoa. Hệ thống có thể phát hiện và phân tích hàng loạt bất thường trên phim X-quang, CT, MRI với độ chính xác cao.

Với link online: một video được nhúng để thay thế ảnh ở phiên bản phiếu khảo sát bản in.



Anh/ Chị đã đọc hiểu các thông tin trên và đồng ý tham gia khảo sát này

☐ Đồng ý

Phần I: Xin anh/ chị hãy thể hiện mức độ đồng ý với những quan điểm/ tuyên bố sau về hệ thống hỗ trợ quyết định y khoa sử dụng AI khi đi khám chữa bệnh
(VD: hệ thống chẩn đoán hình ảnh sử dụng AI)

	Rất <u>không</u> đồng ý	<u>Không</u> đồng ý	Bình thường	Đồng ý	Rất đồng ý
1. Hệ thống hỗ trợ quyết định y khoa sử dụng AI được tạo ra nhằm hỗ trợ người bệnh	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
2. Có thể yên tâm dựa vào hệ thống hỗ trợ quyết định y khoa sử dụng AI	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
3. Hệ thống hỗ trợ quyết định y khoa sử dụng AI đảm bảo an toàn	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
4. Hệ thống hỗ trợ quyết định y khoa sử dụng AI là đáng tin cậy	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
5. Theo tôi, chấp nhận sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh là lựa chọn đúng đắn	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
6. Theo tôi, chấp nhận sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh mang lại nhiều lợi ích	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
7. Theo tôi, chấp nhận sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh là lựa chọn khôn ngoan	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
8. Theo tôi, không nên sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
9. Người thân và gia đình tôi sẽ tán thành việc tôi chấp nhận sử dụng hệ thống hỗ trợ quyết định y khoa	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5

có AI khi đi khám, chữa bệnh					
10. Những người quan trọng với tôi ủng hộ tôi sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
11. Bạn bè và đồng nghiệp của tôi ủng hộ sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
12. Nhìn chung, những người quan trọng với tôi sẽ ủng hộ việc chấp nhận sử dụng hệ thống chẩn đoán hình ảnh có AI trợ giúp khi đi khám, chữa bệnh	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
13. Cũng không dễ để tiếp cận hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh ở cơ sở y tế	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
14. Với tôi, việc sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh là khả thi	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
15. Nếu muốn, việc sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh ở cơ sở y tế là trong khả năng của tôi (khả năng chi trả, tiếp cận...)	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
16. Tôi thấy không gặp khó khăn gì nếu muốn sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám, chữa bệnh ở cơ sở y tế.	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5

Phần II: Ý định chấp nhận hệ thống hỗ trợ quyết định y khoa có sử dụng AI

Xin vui lòng thể hiện mức độ đồng ý với những tuyên bố sau. *Nếu hệ thống hỗ trợ quyết định y khoa có AI có ở cơ sở y tế mà anh/ chị đi khám chữa bệnh:*

	Rất không đồng ý	Không đồng ý	Bình thường	Đồng ý	Rất đồng ý
1. Tôi sẽ chấp nhận sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám chữa bệnh	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
2. Tôi có ý định chấp nhận sử dụng hệ thống hỗ trợ quyết định y khoa có AI khi đi khám chữa bệnh	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
3. Trong lần đi khám chữa bệnh sắp tới, tôi có ý định sẽ sử dụng hệ thống hỗ trợ quyết định y khoa có AI	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
4. Trong tương lai, khi đi khám chữa bệnh tôi sẽ sử dụng hệ thống hỗ trợ quyết định y khoa có AI	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5

Phần III: Quan niệm về công nghệ, con người và về bản thân

Xin anh/ chị vui lòng thể hiện mức độ đồng ý với những tuyên bố sau:

	Rất không đồng ý	Không đồng ý	Bình thường	Đồng ý	Rất đồng ý
1. Các công nghệ mới góp phần nâng cao chất lượng cuộc sống	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
2. Công nghệ giúp mọi việc hiệu quả hơn trong cuộc sống hàng ngày	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
3. Tôi thích sử dụng các công nghệ tiên tiến nhất hiện có	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
4. Tôi thấy thuận tiện hơn nhiều khi sử dụng các sản phẩm/dịch vụ có ứng dụng công nghệ mới nhất	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
5. Công nghệ mới cho phép tôi tùy chỉnh mọi thứ để phù hợp với nhu cầu của riêng tôi	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
6. Con người là mắt xích cuối cùng trong quá trình tiến hóa của tự nhiên & theo quan điểm tôn giáo, là “đỉnh cao của tạo hoá”	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
7. Con người là một sinh vật độc nhất, một sinh vật đặc biệt trong Vũ trụ này	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
8. Chỉ có con người mới có thể hiểu biết thế giới một cách khách quan, như nó vốn có	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
9. Lợi ích của con người quan trọng hơn nhu cầu của bất kỳ sinh vật nào khác	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
10. Việc sử dụng AI ngày càng tăng trong cuộc sống hàng ngày của chúng ta đang gây ra nhiều mất việc làm hơn	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅

	Rất không đồng ý	Không đồng ý	Bình thường	Đồng ý	Rất đồng ý
cho con người					
11. Về lâu dài, AI gây ra mối đe dọa trực tiếp đến sự an toàn và hạnh phúc của con người	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
12. Những tiến bộ gần đây trong công nghệ AI đang thách thức bản chất của con người	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
13. Những tiến bộ công nghệ trong lĩnh vực AI đang đe dọa đến tính độc đáo của con người	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
14. Tôi luôn cố gắng hướng tới một cuộc sống tiết kiệm	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
15. Tôi thấy cần phải thận trọng khi mua và sử dụng các sản phẩm mới	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
16. Tôi thích sử dụng các sản phẩm và dịch vụ mang tính truyền thống	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
17. Đối với tôi, điều quan trọng là phải tôn trọng ý kiến của người khác về bản thân mình	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
18. Đối với tôi, điều quan trọng là phải tuân thủ và bảo tồn các giá trị truyền thống trong các mối quan hệ xã hội	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
19. Tôi thích những người ăn mặc hiện đại và thời trang.	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
20. Tôi nghĩ điều quan trọng là biết tận hưởng cuộc sống	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
21. Tôi thích lối sống hiện đại	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5

	Rất không đồng ý	Không đồng ý	Bình thường	Đồng ý	Rất đồng ý
22. Tôi thích thử các sản phẩm và dịch vụ mới	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
23. Tôi nghĩ rằng những thay đổi sẽ tạo thêm hứng thú cho cuộc sống của mỗi người	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
24. Nếu tôi nghe nói về một công nghệ sức khỏe mới, tôi sẽ tìm cách để trải nghiệm nó.	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
25. Trong số những người bạn của tôi, tôi thường là người đầu tiên trải nghiệm các công nghệ sức khỏe mới.	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
26. Tôi thích trải nghiệm các công nghệ sức khỏe mới.	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5

Phần IV: Thông tin cá nhân

1. Xin anh /chị vui lòng cho biết giới tính của anh/chị:	<input type="checkbox"/> ₁ Nam <input type="checkbox"/> ₂ Nữ
2. Xin vui lòng cho biết tuổi của anh /chị :
3. Xin vui lòng cho biết trình độ học vấn của anh/ chị:	<input type="checkbox"/> ₁ Học PTTH <input type="checkbox"/> ₂ Tốt nghiệp PTTH <input type="checkbox"/> ₃ Tốt nghiệp đại học/cao đẳng <input type="checkbox"/> ₄ Bằng sau đại học (ThS/TS)
4. Xin vui lòng cho biết nghề nghiệp của anh/ chị thuộc nhóm:	<input type="checkbox"/> ₁ Sinh viên <input type="checkbox"/> ₂ Cán bộ quản lý/Chủ đơn vị kinh doanh <input type="checkbox"/> ₃ Nhân viên marketing/sales <input type="checkbox"/> ₄ Nhân viên văn phòng <input type="checkbox"/> ₅ Khác (xin nêu rõ:.....)
5. Xin vui lòng cho biết tôn giáo của anh/ chị	<input type="checkbox"/> ₁ Không <input type="checkbox"/> ₂ Phật giáo <input type="checkbox"/> ₃ Ki tô giáo <input type="checkbox"/> ₄ Khác (xin nêu rõ):...
6. Xin vui lòng cho biết thu nhập trung bình hàng tháng của CÁ NHÂN anh/ chị?	<input type="checkbox"/> ₁ < 5 triệu đồng <input type="checkbox"/> ₂ Từ 5 triệu đồng đến 10 triệu đồng <input type="checkbox"/> ₃ Từ 10 triệu đồng đến 15 triệu đồng <input type="checkbox"/> ₄ Từ 15 triệu đồng đến 20 triệu đồng <input type="checkbox"/> ₅ Từ 20 triệu đồng đến 25 triệu đồng <input type="checkbox"/> ₆ Trên 25 triệu đồng
7. Xin vui lòng cho biết thu nhập trung bình hàng tháng của GIA ĐÌNH anh/ chị?	<input type="checkbox"/> ₁ Dưới 10 triệu đồng <input type="checkbox"/> ₂ Từ 10 triệu đồng đến 20 triệu đồng <input type="checkbox"/> ₃ Từ 20 triệu đồng đến 30 triệu đồng <input type="checkbox"/> ₄ Từ 30 triệu đồng đến 40 triệu đồng <input type="checkbox"/> ₅ Từ 40 triệu đồng đến 50 triệu đồng <input type="checkbox"/> ₆ Trên 50 triệu đồng

Để giúp cho công việc nghiên cứu thuận lợi hơn, xin anh/ chị cho biết tên và địa chỉ liên hệ:

Tên người trả lời:.....

Địa chỉ:.....

Tel.:.....

***XIN TRÂN TRỌNG CẢM ƠN ANH/ CHỊ ĐÃ DÀNH THỜI GIAN HOÀN
THÀNH KHẢO SÁT!***

Appendix 4: Informants overview

ID	Types	Industry	Positions	Background
A	Doctor	Healthcare	Professor, Head of a medical institute	A leading expert in the field of gastroenterology in Vietnam. VP of the Vietnam Gastroenterology Association. Member of a national-level research project on medical AI development
B	Doctor	Healthcare	Associate Professor, Head of Endoscopy Center of Hanoi Medical University Hospital	A reputable expert in the field of gastroenterology in Vietnam and Asia. Lead researcher of a national-level research project on medical AI development; Jointly developed several medical AI products
C	Doctor	Healthcare	Senior medical doctor in Medical Imaging	Senior medical imaging doctors. Had experience with medical AI
D	Doctor	Healthcare	Associate Professor, Head of Medical Imaging Department	Head of Medical Imaging Department at Hanoi Medical University Hospital; Co-developed several AI products in medical imaging
E	Doctor	Healthcare	PhD, Vice Head of Medical Imaging Department	Head of Medical Imaging Department at Hanoi Medical University Hospital; Co-developed

ID	Types	Industry	Positions	Background
				several AI products in medical imaging
F	Doctor	Healthcare	Senior medical doctor in Endoscopy	Senior endoscopist
G	Doctor	Healthcare	Senior medical doctor in Endoscopy, Head of the Endoscopy department	Senior endoscopist
H	Doctor	Healthcare	Experienced medical doctor in endoscopy	Experienced endoscopist; Member of a few research projects on medical AI development
I	Doctor	Healthcare	Junior medical doctor in endoscopy	Junior endoscopist
J	Doctor	Healthcare	Senior medical doctor in Endoscopy	Experienced endoscopist; Member of a few research projects on medical AI development
K	Policymaker	Government	Government official	Government official at the Ministry of Health of Vietnam
L	Policymaker	Government	Government official, Head of a department at the Ministry of Health	Government official, Director of the Department of Science, Technology, and Education at the Ministry of Health of Vietnam
M	Industry	Medical Technology	VP/ Entrepreneur	Founder of a leading Vietnamese medical technology startup in Vietnam; Vice President

ID	Types	Industry	Positions	Background
				of a global giant technology company
N	Industry	Healthcare	Founder/ Medical Supplier	Founder; Medical Supplier
O	Consumer	Marketing	Head of Marketing department	40 years old tech enthusiast consumer
P	Consumer	Office	Legal Staff	27 years old tech enthusiast consumer
Q	Consumer	Government	Diplomatic officer	28 years old tech enthusiast consumer