ÓBUDAI EGYETEM
ÓBUDA UNIVERSITY

PhD Dissertation

Bekesy, Mariann

ARTIFICIAL INTELLIGENCE IN HEALTH-RELATED INFORMATION USE:

A CONSUMER PERSPECTIVE FROM YOUNG ADULTS

Supervisors:
Dr. Szigeti, Orsolya habil, PhD Obuda University
Dr. Szabó, István habil, PhD Obuda University

Doctoral School of Innovation Management

Budapest, 2026.04. 13.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

Artificial intelligence (AI) has become one of the most transformative technologies in contemporary society, reshaping how individuals access information, make decisions, and interact with expert knowledge. In health-related contexts, AI-driven systems increasingly influence how people interpret symptoms, assess their health status, and engage with medical information. From a scientific perspective, this transformation raises critical questions regarding user attitudes, trust, and acceptance, as these factors fundamentally determine how AI technologies are integrated into everyday health communication (Lim and Schmälzle, 2023; Pavaloiu and Ioanid, 2024).

The topic is also highly relevant from a socio-economic perspective. AI-based health-related applications have the potential to alter healthcare utilization patterns, information-seeking behavior, and individual engagement with health-related information and decision-making. As digital health tools become more widespread, individuals increasingly act as active health consumers who evaluate and interpret AI-generated content rather than relying exclusively on traditional medical authority (World Health Organization, 2023; OECD, 2023). In this context, generational differences are particularly important, as younger cohorts tend to adopt digital technologies faster and integrate them into everyday decision-making processes (Pew Research Center, 2019).

Recent academic research has examined several dimensions of AI use in healthcare communication, including perceived usefulness, trust, ethical concerns, and user acceptance. Studies have highlighted both the opportunities offered by AI-generated health messages and the risks associated with probabilistic language generation, such as misinformation and hallucinated outputs (Howard *et al.*, 2024; Rodrigues *et al.*, 2024). However, empirical findings remain fragmented, especially with regard to conversational, consumer-facing AI systems. Moreover, existing research often treats users as a relatively homogeneous population, despite growing evidence that age and generational background significantly shape technology acceptance and trust (König and Neumayr, 2022; Cecconi *et al.*, 2025).

Within the broad spectrum of artificial intelligence applications, this study focuses specifically on ChatGPT. This focus is justified by ChatGPT's widespread accessibility, conversational interface, and increasing use as a general-purpose AI tool for health-related information seeking. Unlike specialized clinical decision-support systems, ChatGPT operates as a publicly available platform that users may consult independently, without professional mediation. As such, it represents a particularly relevant case for examining attitudes toward AI in health status–related contexts (Pavaloiu and Ioanid, 2024).

Accordingly, the aim of this study is to provide an initial empirical exploration of young consumers' attitudes toward the use of artificial intelligence in health status–related information seeking, using ChatGPT as an illustrative example. By emphasizing generational differences in trust and acceptance (Rodrigues *et al.*, 2024; Tan and Ong, 2024), the research seeks to contribute to a more nuanced understanding of how AI-based health communication tools are perceived and used in contemporary digital societies.

2. AIMS AND OBJECTIVES

The primary aim of this doctoral dissertation is to examine public attitudes toward the use of ChatGPT for health-related purposes in Hungary, with particular emphasis on the influence of demographic characteristics on acceptance, trust, and intention to use generative artificial intelligence (AI) in healthcare contexts. In addition to primary empirical research, the dissertation also aims to systematically review and critically analyse existing international literature on AI acceptance in healthcare in order to contextualise the empirical findings and identify theoretical and empirical gaps (Pavaloiu and Ioanid, 2024; Rodrigues et al., 2024).

In order to contribute to the broader literature on AI acceptance, the dissertation also aim to provide context-specific insights. By focusing on Hungary - a country characterised by relatively high uncertainty avoidance and a strong reliance on institutionalised healthcare systems - the study seeks to contribute context-specific evidence to the international literature on AI acceptance in healthcare (OECD, 2024). While many existing studies focus on healthcare professionals, students, or clinical applications, this dissertation adopts a population-level perspective by examining how members of the general public perceive conversational AI tools in everyday health-related situations (Cecconi *et al.*, 2025).

Previous research shows that acceptance of health-related technologies is not determined solely by technical performance. Instead, it is shaped by the interaction of demographic characteristics, perceived usefulness, ease of use, trust, cultural values, and institutional context (König and Neumayr, 2022; Chi *et al.*, 2024). Technology acceptance models such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) explicitly recognise the moderating role of demographic variables, indicating that different population groups may respond differently to the same technology (Venkatesh *et al.*, 2003).

This dissertation aims to situate both the secondary literature review and the primary empirical findings within established technology acceptance frameworks, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT). Through this approach, the study contributes to the empirical evaluation and contextual adaptation of technology acceptance models in the field of generative AI in healthcare (Venkatesh *et al.*, 2003; Venkatesh *et al.*, 2016). At the same time, the emergence of generative AI systems introduces new characteristics that may influence technology acceptance in ways not fully captured by earlier digital health technologies. Generative AI systems such as ChatGPT have rapidly become part of public awareness and everyday use, including health information seeking.

Unlike earlier digital health technologies, these systems rely on natural language interaction, provide immediate responses, and often appear authoritative due to their fluent and confident style of communication. These characteristics raise specific concerns related to trust, responsibility, and user understanding, particularly in healthcare contexts where information accuracy and accountability are essential (Howard et al., 2024; Tan and Ong, 2024).

Despite the growing body of research on AI in healthcare and technology acceptance, several gaps remain. Population-level studies on generative AI are still limited, Central and Eastern European countries are underrepresented in international research, and the relative importance of formal education compared to practical digital experience remains unclear in the context of widely accessible conversational AI tools (Rodrigues *et al.*, 2024; OECD, 2024). These gaps provide the conceptual basis for the objectives of this dissertation.

Based on the indentified research gaps and theoritical considerations discussed above, the present dissertation aims to examine the selected topic in a structured and comprehensive manner. In order to achieve this, the following objectives have been defined:

- **Objective 1**: to synthesise and critically review international literature on AI acceptance in healthcare, with particular attention to generative AI and conversational systems.
- **Objective 2:** to describe general public attitudes toward ChatGPT as a health-related tool in Hungary, including perceived usefulness, ease of use, reliability, and willingness to use.
- **Objective 3**: to examine the influence of demographic characteristics on acceptance, trust, and intention to use ChatGPT, treating demographic factors as a broad explanatory category rather than as isolated variables.
- **Objective 4:** to examine the role of trust as a key determinant of acceptance of ChatGPT in healthcare contexts.
- **Objective 5**: to assess the applicability of the UTAUT framework in explaining acceptance of ChatGPT in Hungary, with particular attention to the moderating role of demographic characteristics.

3. LITERATURE REVIEW

3.1 Artificial Intelligence and Digital Transformation

Contemporary society is characterized by rapid technological change, increasing demands for efficiency, and a growing expectation of immediate solutions across nearly all areas of everyday life. Digital transformation has become a defining feature of economic, social, and institutional development, fundamentally reshaping how individuals work, communicate, learn, and access services. Internet-based platforms, cloud technologies, and data-driven systems have expanded at an unprecedented pace, enabling new forms of interaction between humans and machines. These developments are not limited to highly specialized industrial environments but increasingly shape routine activities such as information seeking, communication, decision-making, and service use (Vial, 2019).

Human–machine interaction has thus become an integral part of modern life. Interactions range from relatively simple automated systems, such as recommendation algorithms or customer service chatbots, to more complex forms of collaboration involving intelligent software agents, robotics, and autonomous systems. In the literature, these interactions are often framed as a source of significant opportunity. Intelligent systems can enhance productivity, reduce routine workloads, support complex decision-making processes, and compensate for human cognitive limitations, particularly in data-intensive environments (Autor et al., 2020). At the same time, digital transformation also introduces uncertainty and ambivalence. While individuals increasingly recognize the efficiency and convenience offered by intelligent technologies, they often express mixed feelings regarding the growing presence of machines in everyday life, especially when these systems operate autonomously or opaquely.

Empirical research consistently shows that technological acceptance is unevenly distributed across populations. Individuals with higher levels of technological knowledge, digital skills, and prior experience tend to adapt more easily to technological change and are more likely to perceive its benefits. In contrast, limited familiarity with digital systems is frequently associated with skepticism, anxiety, or resistance (Gou et al., 2021; Szatmáry and Szikora, 2023). These differences highlight that digital transformation is not solely a technical process but also a social one, shaped by individual competencies, cultural norms, and institutional contexts.

Within this broader landscape of digital transformation, artificial intelligence (AI) has emerged as one of the most influential and rapidly developing technological drivers. Artificial intelligence refers to a field of computer science focused on the development of systems capable of performing tasks that traditionally require human intelligence. These tasks include learning from experience, reasoning, problem-solving, perception, and language understanding. Unlike earlier forms of automation that relied on predefined rules and static programming, AI systems are designed to respond dynamically to inputs from their environment or from large datasets and to improve their performance through iterative learning processes (Russell and Norvig, 2016).

The adaptive capacity of AI systems represents a fundamental shift in the relationship between humans and technology. Rather than merely executing predefined instructions, AI systems can identify patterns, adjust their behavior, and generate outputs that were not explicitly programmed in advance. This capacity enables their application across a wide range of domains, including finance, transportation, manufacturing, education, and healthcare. Importantly, AI systems do not operate independently of human input. Their design, training, and deployment are shaped by human decisions, values, and institutional frameworks, which in turn influence how these systems are perceived and used in practice (Floridi et al., 2018).

The development and functioning of AI systems rely heavily on mathematical modeling, computer programming, and statistical methods. During the learning process, AI systems are trained on large volumes of data through repetitive computational procedures that allow them to detect patterns, identify correlations, and reduce errors over time. This process, commonly referred to as machine learning, enables systems to improve performance without explicit reprogramming. Deep learning, a subset of machine learning, uses multilayer neural networks to model complex relationships within large datasets, making it particularly effective for tasks such as image recognition, speech processing, and language generation (Dean et al., 2012; Litjens et al., 2017).

Artificial intelligence is therefore best understood as an umbrella term encompassing several interrelated subfields. Machine learning focuses on data-driven learning processes, deep learning emphasizes complex neural network architectures, and natural language processing (NLP) enables machines to understand, interpret, and generate human language (Table 1). NLP plays a particularly important role in human–machine interaction, as it allows users to communicate with systems using natural language rather than specialized technical commands. This significantly lowers the barrier to entry for non-expert users and facilitates the integration of AI into everyday contexts (Jurafsky and Martin, 2023).

Table 1: Main subfields of artificial intelligence and typical application areas

AI subfield	Core characteristics	Typical application areas
Machine learning	Algorithms that learn patterns from data without explicit programming	Prediction, classification, risk assessment
Deep learning	Multi-layer neural networks capable of modeling complex data structures	Medical imaging, speech recognition
Natural language processing (NLP)	Computational processing and generation of human language	Chatbots, virtual assistants, text analysis
Conversational AI	NLP-based systems enabling interactive dialogue with users	ChatGPT, healthcare chatbots

Source: Compiled by the author based on Russell and Norvig (2016); Dean et al. (2012); Litjens et al. (2017); Deng and Lin (2023)

Recent advances in NLP have led to the development of large language models trained on extensive corpora of textual data. These models are capable of generating coherent, context-sensitive responses that resemble human conversation. They can adjust tone, style, and level of detail depending on the context of interaction, which makes them particularly suitable for applications involving information exchange, guidance, and user support. As a result, conversational AI systems have become increasingly visible and accessible to the general public (Deng and Lin, 2023).

ChatGPT represents one of the most prominent examples of this new generation of conversational AI. Built on the Generative Pre-trained Transformer (GPT) architecture, ChatGPT is a deep learning–based NLP system trained on vast datasets containing diverse forms of written communication. Its design enables it to generate contextually relevant responses to user queries and to maintain conversational coherence across multiple turns of interaction. Unlike earlier rule-based chatbots, ChatGPT can adapt its responses based on the perceived intent of the user and the evolving context of the conversation, which contributes to a more natural and engaging interaction experience (Brown et al., 2020).

The widespread availability of conversational AI tools reflects broader trends in digital transformation, particularly the emphasis on intuitive, user-friendly interfaces. However, this accessibility also raises important questions regarding user understanding and expectations. Because conversational AI systems communicate fluently and confidently, users may attribute levels of competence, authority, or intentionality that exceed the system's actual capabilities.

This phenomenon, often described as automation bias or overreliance, can lead users to place unwarranted trust in AI-generated outputs (Shin, 2021).

Research on human–machine collaboration demonstrates that acceptance of intelligent systems is not determined solely by technical performance or accuracy. Social, cognitive, and cultural factors play a crucial role in shaping how individuals interpret and engage with AI-based technologies. Perceived usefulness, perceived ease of use, trust, perceived risk, and prior experience all influence technology acceptance and use. In many cases, resistance to AI does not stem from opposition to technology itself but from concerns related to transparency, accountability, and loss of human control (Meissner et al., 2020; Mareček-Kolibiský et al., 2024).

Importantly, attitudes toward AI are embedded within broader social and institutional environments. Cultural norms, regulatory frameworks, media narratives, and public discourse shape how technological change is perceived and evaluated. In societies characterized by higher levels of uncertainty avoidance or strong reliance on institutional authority, individuals may approach autonomous or self-learning systems with greater caution. Conversely, environments that emphasize innovation, experimentation, and technological optimism may foster more positive orientations toward AI-driven solutions (Békésy et al.,2024).

Taken together, artificial intelligence should be understood as both a technological and a social phenomenon embedded within ongoing processes of digital transformation. While AI offers substantial potential to enhance efficiency, accessibility, and problem-solving capacity, its integration into everyday life also raises important questions related to trust, understanding, and acceptance. These dynamics provide the conceptual foundation for examining the role of conversational AI systems such as ChatGPT in health-related information contexts, which will be explored in the following chapters.

3.2 ChatGPT and Health-Related Information

Building on the broader processes of digital transformation and the increasing presence of artificial intelligence in everyday life, conversational AI systems have gained particular relevance in the context of health-related information and communication. Access to health information has changed substantially over the past two decades. Individuals no longer rely exclusively on healthcare professionals as primary sources of medical knowledge but increasingly turn to digital platforms, search engines, and online tools to seek information about symptoms, treatments, preventive measures, and lifestyle-related health issues. This shift has been described in the literature as a transition toward more active and self-directed health information seeking, often referred to as online health information seeking behavior (OHISB) (Jacobs et al., 2017).

Health-related information seeking is closely linked to broader societal changes, including rising health awareness, increasing prevalence of chronic conditions, and growing pressure on healthcare systems. As healthcare resources become strained, individuals are encouraged to take a more proactive role in managing their own health. Digital technologies play a central role in this process by providing rapid and convenient access to information. However, the quality, accuracy, and interpretability of online health information vary widely, which raises concerns regarding misinformation, misunderstanding, and inappropriate self-diagnosis (Diviani et al., 2015).

Artificial intelligence has increasingly been introduced as a potential solution to some of these challenges. AI-driven systems can process large volumes of medical and health-related data, personalize information delivery, and adapt responses to individual users. In contrast to static websites or generic information portals, conversational AI systems offer interactive dialogue, allowing users to ask follow-up questions, clarify uncertainties, and receive tailored explanations. These features make conversational AI particularly attractive in health-related contexts, where users often seek reassurance, clarification, and contextualized guidance rather than isolated facts (Lim and Schmälzle, 2023).

ChatGPT represents a prominent example of such conversational AI systems. As a large language model based on deep learning and natural language processing, ChatGPT is capable of generating human-like responses to a wide range of queries. In health-related contexts, this means that users can engage in dialogue about symptoms, medical terminology, treatment options, or preventive behaviors using everyday language. This conversational format lowers barriers to access, especially for individuals who may feel intimidated by medical jargon or hesitant to consult healthcare professionals for non-urgent concerns (Pavaloiu and Ioanid, 2024).

One of the most frequently cited advantages of ChatGPT in health-related information provision is its constant availability. Unlike healthcare professionals, who are constrained by time, location, and institutional structures, conversational AI systems can be accessed at any time and from virtually any location with an internet connection. This accessibility is particularly relevant for individuals living in underserved or rural areas, as well as for those seeking information outside of regular healthcare hours. Studies in public health communication suggest that such availability can reduce informational inequalities, at least at the level of initial information access (Benke and Benke, 2018).

Beyond accessibility, ChatGPT can support comprehension by translating complex medical concepts into more understandable language. Health information is often difficult to interpret due to specialized terminology and abstract explanations. Conversational AI systems can rephrase content, provide examples, and adapt explanations to the user's perceived level of understanding. This function is closely related to the concept of health literacy, which refers to individuals' ability to obtain, process, and understand basic health information needed to make appropriate health decisions (Nutbeam, 2000). Digital tools that enhance comprehension may therefore contribute positively to health literacy, particularly among populations with limited medical knowledge (WHO, 2023).

ChatGPT can also facilitate iterative learning through follow-up questions. Unlike static information sources, conversational AI allows users to refine their queries based on previous responses, creating a dynamic exchange. This interaction mirrors aspects of human communication and can support deeper engagement with health-related content. Empirical research on interactive health communication indicates that such dialogic formats may enhance user satisfaction and perceived usefulness compared to one-directional information delivery (Oh et al., 2021).

In addition to general health information, ChatGPT has been explored in more specific domains, such as lifestyle counseling, chronic disease management, and mental health support. For example, AI-driven conversational agents have been used to promote physical activity, healthy eating, and medication adherence by providing reminders, motivational messages, and personalized feedback. Although these applications vary in effectiveness, evidence suggests that conversational agents can play a supportive role in encouraging health-promoting behaviors when appropriately designed and monitored (Alanezi, 2024).

Despite these potential benefits, the use of ChatGPT for health-related information also raises important limitations and risks. One central concern relates to the accuracy of AI-generated content. Large language models generate responses based on patterns in training data rather than verified medical knowledge. As a result, they may produce plausible-sounding but incorrect or misleading information, a phenomenon often referred to as "hallucination" in the AI literature. In health contexts, such inaccuracies can have serious consequences if users rely on incorrect advice for decision-making (Howard et al., 2024).

Another limitation is that ChatGPT does not possess true understanding or clinical judgment. While it can simulate empathetic communication and provide generalized information, it cannot assess individual medical histories, perform physical examinations, or consider contextual factors in the way a healthcare professional can. For this reason, the literature consistently emphasizes that conversational AI should be used as a supplementary source of information rather than a replacement for professional medical advice (Sallam, 2023).

International policy organizations have increasingly addressed the growing role of AI in health information provision. Reports by the World Health Organization and the OECD highlight both the opportunities and challenges associated with AI-supported health communication. On the one hand, AI tools may improve access to information and support patient empowerment. On the other hand, they may exacerbate inequalities if digital literacy is unevenly distributed or if vulnerable populations lack the skills to critically evaluate AI-generated content (OECD, 2024; WHO, 2023).

Empirical studies examining public attitudes toward ChatGPT in healthcare contexts reveal mixed perceptions. While many users appreciate the convenience and responsiveness of conversational AI, others express concerns regarding reliability, data protection, and the absence of human judgment. A large-scale survey by Platt et al. (2024) found that overall comfort with ChatGPT in healthcare-related use remains moderate, with significant variation across demographic groups. These findings underscore that acceptance of conversational AI in health contexts cannot be assumed but must be understood in relation to broader social, cultural, and individual factors.

Therefore, even if ChatGPT occupies a complex position within contemporary health information ecosystems by offering significant potential to enhance access, comprehension, and engagement with health-related information, particularly in non-urgent and educational contexts, at the same time, its limitations highlight the importance of clear boundaries, ethical safeguards, and informed user expectations.

3.3 Trust, Risks, and Ethical Concerns in AI-Based Health Communication

Artificial intelligence–based health communication tools, including conversational AI systems such as ChatGPT, introduce new opportunities but also complex challenges related to trust, perceived risk, and ethical responsibility. These dimensions are particularly salient in healthcare contexts, where users are often vulnerable, information asymmetry is high, and the consequences of misinformation may directly affect well-being (Rodrigues et al., 2024).

3.3.1 Trust in AI-Based Health Communication

Trust is widely regarded as a foundational element of technology acceptance, especially in domains characterized by uncertainty and potential harm. In organizational and psychological research, trust is commonly defined as a willingness to accept vulnerability based on positive expectations regarding the behavior or intentions of another party (Mayer et al., 1995). Applied to artificial intelligence, trust refers to the extent to which users are willing to rely on an AI system's outputs despite limited insight into its internal decision-making processes.

In healthcare communication, trust in AI differs fundamentally from interpersonal trust between patients and healthcare professionals. While physician–patient trust is grounded in professional accountability, ethical codes, and personal interaction, trust in AI is mediated through technical systems and interfaces. Users must infer trustworthiness from observable cues such as response coherence, linguistic fluency, and perceived expertise (Lee and See, 2004). Research shows that conversational AI systems often benefit from a "fluency effect," whereby well-articulated responses are perceived as more credible regardless of their factual accuracy (Shin, 2021).

Trust in AI-based health communication also carries a normative dimension. Users frequently expect AI systems to align with core medical values, including beneficence, non-maleficence, and respect for autonomy. These expectations are often implicit but strongly influence user judgments. When AI-generated responses appear careless, overly confident, or dismissive of uncertainty, perceived trustworthiness may decline sharply (Floridi et al., 2018). Importantly, trust is not static but evolves over time. Initial trust may be shaped by reputation, media narratives, or institutional endorsement, while sustained trust develops through repeated interaction and experiential validation. In health-related contexts, even isolated negative experiences may disproportionately undermine trust, reflecting low tolerance for error in situations involving health risks (Shin and Park, 2019).

3.3.2 Risk, Ethical Concerns, and Contextual Dimensions of AI-Based Health Communication

Closely connected to trust is the concept of perceived risk. In risk theory, risk is generally understood as the combination of the probability of an adverse event and the severity of its potential consequences (Aven, 2016). In healthcare communication, risk perception is often heightened because incorrect or misleading information may directly affect health-related decisions.

One of the most frequently discussed risks of conversational AI in healthcare is informational inaccuracy. Large language models generate responses based on statistical patterns in training data rather than verified medical reasoning. This can result in partially correct, outdated, or fabricated information. The phenomenon of AI "hallucination," in which systems produce plausible but false content, poses particular risks when users lack the expertise to critically evaluate outputs (Howard et al., 2024).

Risk perception is further influenced by automation bias, a cognitive tendency whereby individuals over-rely on automated systems and discount contradictory information from other sources. In health contexts, automation bias may delay professional consultation or encourage inappropriate self-diagnosis and self-treatment (Lyell and Coiera, 2017).

Beyond informational risks, behavioral and psychological risks must also be considered. AI-generated health information can shape emotions, perceptions, and behaviors in unintended ways. Overly reassuring responses may discourage timely care-seeking, while alarmist messages may increase anxiety or lead to unnecessary medical interventions. Studies in digital health communication suggest that such effects vary significantly across individuals and demographic groups (Blease et al., 2023).

Ethical concerns provide a broader normative framework within which trust and risk are evaluated. Ethics in AI-based healthcare communication refers to the moral principles guiding system design, data use, and interaction with users, particularly when these systems influence health-related understanding and decision-making (Floridi et al., 2018).

Data privacy is one of the most prominent ethical issues. Health-related interactions often involve sensitive personal information, yet users may have limited awareness of how their data are collected, processed, and stored. Concerns about surveillance, secondary data use, and loss of control over personal information significantly influence willingness to engage with AI-based health tools (Sallam, 2023).

Accountability represents another major ethical challenge. In traditional healthcare settings, responsibility for medical advice is clearly assigned to licensed professionals and institutions. In contrast, AI-mediated health communication blurs responsibility boundaries. When harm occurs, it remains unclear whether responsibility lies with developers, platform providers, healthcare institutions, or users themselves. This ambiguity undermines ethical clarity and weakens trust (Jobin et al., 2019).

Ethical discussions also emphasize the risk of overreliance on AI systems. Excessive dependence on conversational AI may reduce users' critical engagement and undermine informed decision-making. Ethical guidelines therefore stress the importance of transparency, clear communication of system limitations, and reinforcement of AI's supplementary role rather than replacement of professional medical advice (WHO, 2023).

Trust, perceived risk, and ethical concerns are deeply interconnected and should not be treated as isolated dimensions. High perceived risk tends to erode trust, while strong ethical safeguards—such as transparency, accountability, and privacy protection—can mitigate risk perceptions and foster trust. Conversely, ethical ambiguity may amplify perceived risks even when technical performance is high (Glikson and Woolley, 2020).

From a user perspective, trust often functions as a heuristic for managing complexity. When ethical principles are visible and risks are openly acknowledged, users may feel more confident engaging with AI-based health communication tools. Cultural and institutional contexts further shape these perceptions. Societies with high uncertainty avoidance or strong reliance on professional authority may exhibit greater caution toward autonomous AI systems, while innovation-oriented environments may foster more positive attitudes (Rodrigues et al., 2024).

Empirical research from Central and Eastern Europe provides important contextual insights into how trust, perceived risks, and ethical concerns shape attitudes toward artificial intelligence in healthcare. While global discussions on AI ethics often emphasize universal principles, regional studies suggest that historical legacies, institutional trust, and regulatory maturity significantly influence how AI-based health technologies are perceived and evaluated in practice (Jobin et al., 2019; Tachkov et al., 2022; Rodrigues et al., 2024).

Several studies conducted in the Central and Eastern European region indicate that trust in AI is closely tied to concerns about transparency, accountability, and professional oversight. A cross-sectional study among Croatian and Slovenian medical faculty members found broad support for ethical principles such as patient autonomy, fairness, and non-maleficence, alongside persistent concerns regarding the opacity of AI systems and the potential erosion of physicians’ decision-making authority (Grosek, Knez and Kocbek, 2024). These findings suggest that ethical acceptance of AI in healthcare is conditional upon clear governance frameworks and the preservation of human responsibility in clinical decision-making processes (Jobin, Ienca and Vayena, 2019; Grosek, Knez and Kocbek, 2024).

Research focusing on the general population further underscores the centrality of trust and perceived control in shaping attitudes toward AI-based health technologies. A qualitative study conducted in Poland revealed that lay users often associate AI in healthcare with uncertainty, reduced transparency, and loss of personal agency, particularly when decision-making processes are not easily understandable or explainable (Smoła et al., 2025). Participants frequently raised questions about who bears responsibility for AI-generated recommendations and whether automated systems are capable of adequately accounting for individual patient contexts, which in turn heightened perceptions of risk and skepticism toward AI-supported health communication (Smoła et al., 2025; Shin, 2021).

From a system-level perspective, studies examining health technology assessment and policy environments in Central and Eastern Europe identify structural barriers that indirectly affect public trust in AI. An international comparative analysis of HTA practices in the region highlights limited data availability, insufficient methodological transparency, and regulatory uncertainty as key obstacles to the responsible implementation of AI-based health technologies (Tachkov et al., 2022). These systemic limitations may reinforce perceptions of risk and undermine confidence in AI-supported healthcare innovations among both healthcare professionals and the general public (Tachkov et al., 2022; OECD, 2024).

Hungarian-specific empirical evidence further supports the relevance of trust, risk, and ethical concerns in shaping AI acceptance. A recent survey conducted among Hungarian healthcare professionals reported generally positive attitudes toward the potential benefits of artificial intelligence, particularly in relation to efficiency and diagnostic support, while simultaneously revealing significant reservations regarding data protection, legal accountability, and ethical responsibility (Magyary et al., 2025). These findings indicate that even among expert users, trust in AI systems remains conditional and strongly dependent on institutional safeguards and ethical governance mechanisms (Magyary et al., 2025; Glikson and Woolley, 2020).

3.4 Attitudes Toward AI and Health Technologies

To fully understand public acceptance or resistance to conversational AI systems such as ChatGPT in health-related contexts, it is necessary to examine attitudes as a higher-order construct that integrates beliefs, emotions, and behavioral intentions.

Attitudes function as psychological orientations that shape how individuals interpret technological developments, evaluate potential benefits and risks, and ultimately decide whether to adopt or reject new systems. In healthcare, where technologies intersect with deeply personal concerns related to health, vulnerability, and well-being, attitudes toward AI are especially consequential (Holden and Karsh, 2010). The following section therefore examines how attitudes toward artificial intelligence and health technologies are conceptualized and how they influence technology acceptance in healthcare contexts.

3.4.1 Conceptualizing Attitudes Toward Artificial Intelligence

In social psychology, attitude is commonly defined as a relatively stable evaluation of an object, idea, or technology that encompasses cognitive, affective, and behavioral components. According to the Cambridge Dictionary, attitude refers to "a feeling or opinion about something or someone, or a way of behaving that is caused by this," and is further described as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (Cambridge Dictionary, 2026). This definition highlights that attitudes are not limited to rational judgments but also include emotional reactions and predispositions toward action.

In the context of technology acceptance, attitudes have long been recognized as key predictors of behavioral intention and actual use. Early models such as the Technology Acceptance Model (TAM) conceptualized attitude as a mediating variable between beliefs about usefulness and ease of use and the intention to adopt a technology (Davis, 1989). Although later models sometimes deemphasized explicit attitude constructs, empirical research continues to demonstrate that attitudes remain highly relevant, particularly in complex and sensitive domains such as healthcare (Holden and Karsh, 2010).

Attitudes toward artificial intelligence are shaped by a combination of individual experience, societal discourse, and broader cultural narratives. Public perceptions of AI often oscillate between optimism and concern. On the one hand, AI is associated with innovation, efficiency, and progress; on the other hand, it is frequently linked to fears of loss of control, dehumanization, and unintended consequences (Fast and Horvitz, 2017). These ambivalent representations contribute to heterogeneous attitudes across populations.

Empirical studies indicate that individuals' attitudes toward AI are strongly influenced by their level of technological familiarity and digital literacy. People who have greater exposure to digital technologies and a better understanding of how AI systems function tend to express more positive attitudes and lower levels of anxiety. In contrast, limited knowledge is often associated with uncertainty, skepticism, and resistance (Gou et al., 2021; Kelly et al., 2023). This pattern underscores the importance of cognitive factors in attitude formation.

Media representations also play a significant role. Sensationalist narratives emphasizing either utopian or dystopian outcomes can distort public understanding and contribute to polarized attitudes. Research suggests that balanced and transparent communication about AI capabilities and limitations is essential for fostering informed and realistic attitudes (Shin, 2021).

3.4.2 Attitudes Toward Artificial Intelligence in Healthcare Contexts

Attitudes toward artificial intelligence in healthcare differ in important ways from attitudes toward AI in other domains. Healthcare technologies are evaluated not only in terms of efficiency or convenience but also in relation to trust, safety, and ethical acceptability. Individuals tend to apply stricter standards when assessing technologies that influence health-related decisions, reflecting the higher stakes involved (Blease et al., 2023).

Studies show that while many people recognize the potential benefits of AI in healthcare—such as improved access to information, faster diagnostics, and personalized support—they simultaneously express concerns about accuracy, accountability, and the erosion of human judgment. These mixed attitudes are particularly pronounced in relation to AI systems that directly interact with patients or provide health-related advice (Fritsch et al., 2022).

Conversational AI systems occupy a unique position within this landscape. Unlike clinical decision-support tools used by professionals, systems such as ChatGPT interact directly with lay users and communicate in natural language. This increases accessibility but also raises expectations regarding empathy, understanding, and responsibility. As a result, attitudes toward conversational AI are often shaped by users' subjective interaction experiences rather than by objective performance metrics alone (Glikson and Woolley, 2020).

Several factors contribute to the formation of attitudes toward ChatGPT in health-related contexts. Individual characteristics such as education, age, and prior experience with technology play an important role. Higher educational attainment and greater digital competence are generally associated with more positive attitudes, as they facilitate critical evaluation and reduce uncertainty (Khairan et al., 2021; Edelman, 2020).

Trust, as discussed in the previous chapter, is a particularly strong determinant. Users who perceive ChatGPT as reliable, transparent, and ethically aligned are more likely to develop favorable attitudes toward its use in healthcare. Conversely, concerns about data privacy, misinformation, or lack of accountability tend to foster negative attitudes, even among technologically experienced users (Sallam, 2023).

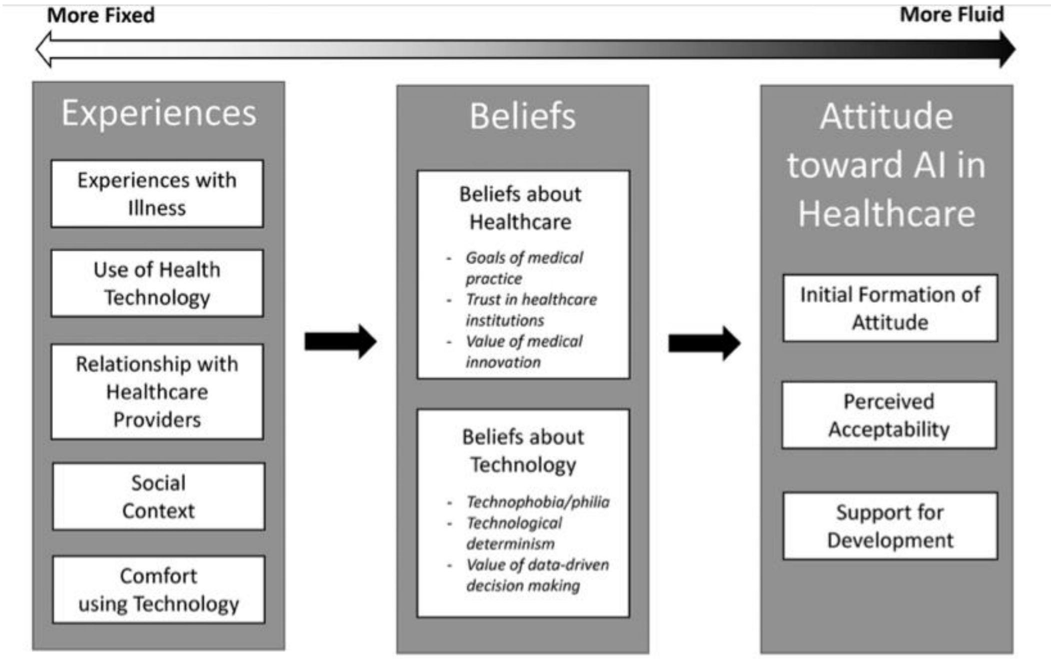
Contextual factors also matter. Attitudes toward ChatGPT may differ depending on whether the system is perceived as a supplementary information source or as a substitute for professional care. Research consistently shows higher acceptance when AI is framed as supporting, rather than replacing, healthcare professionals (WHO, 2023).

Attitudes also serve as an important bridge between underlying beliefs and actual behavior. In acceptance models, they integrate cognitive evaluations (e.g., perceived usefulness), affective responses (e.g., trust or anxiety), and normative considerations (e.g., ethical acceptability). In health-related AI use, this integrative function is especially relevant because users must weigh potential benefits against perceived risks and moral concerns (Venkatesh et al., 2016).

Empirical evidence suggests that positive attitudes toward AI-based health technologies are associated with higher willingness to use such systems for non-urgent health information, lifestyle guidance, and general health education. Negative attitudes, by contrast, are linked to avoidance behavior and preference for exclusively human-mediated communication (Platt et al., 2024).

Attitudes toward AI and health technologies therefore represent a complex and multidimensional construct shaped by cognitive, emotional, and ethical considerations. This relationship between beliefs, attitudes, and behavioral intention is illustrated in Figure 1, which presents a conceptual framework for understanding how patients evaluate artificial intelligence in healthcare.

Figure 1: Proposed conceptual framework for understanding how patients evaluate AI in healthcare



Souce: Adapted from McCradden et al. (2022)

As shown in Figure 1, attitudes function as an intermediary mechanism linking individual beliefs, trust-related perceptions, and behavioral intentions regarding AI use in healthcare. The framework highlights that users evaluate AI technologies not only through functional considerations such as usefulness, but also through broader perceptions of trustworthiness, risk, and ethical legitimacy. These attitudinal processes ultimately influence whether individuals are willing to engage with AI-based health communication tools such as ChatGPT.

This attitudinal perspective provides the conceptual foundation for the subsequent chapters, which examine how attitudes toward ChatGPT vary across demographic groups—particularly by gender, generation, and educational background—and how these differences can be interpreted within established technology acceptance frameworks.

3.5 Conceptual Models of AI Acceptance

Understanding why individuals accept or reject artificial intelligence in healthcare requires robust conceptual frameworks that go beyond descriptive observations. Technology acceptance models provide structured explanations of how beliefs, attitudes, and contextual factors shape behavioral intention and actual use. In healthcare, where AI applications may influence diagnosis, treatment decisions, and personal health behaviors, acceptance is particularly complex and value-laden (Holden and Karsh, 2010; Rodrigues et al., 2024). Traditional models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) offer a theoretical foundation for explaining adoption processes. However, recent research increasingly suggests that these models must be extended to capture trust-related, ethical, and literacy-based dimensions relevant to AI-based health communication.

3.5.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), is one of the earliest and most influential frameworks for explaining individual adoption of information systems. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of users' attitudes toward a technology, which subsequently shape behavioral intention and actual usage (Davis, 1989). Table 2 presents the conceptual structure of TAM and illustrates the relationships between its main constructs.

Table 2: Conceptual structure of TAM

Construct	Definition	Relationship
Perceived Ease of Use (PEOU)	The degree to which a person believes that using a system would be free of effort	Perceived Usefulness
Perceived Usefulness (PU)	The degree to which a person believes that using a system enhances performance	Attitude toward Use
Attitude toward Use	Overall positive or negative evaluation of using the system	Behavioral Intention
Behavioral Intention to Use	Individual's intention to use the technology	Actual Use
Actual Use	Real or intended use of the technology	Outcome variable

Source: Author's own work based on Davis (1989)

As illustrated in Table 2, TAM assumes a rational decision-making process in which individuals evaluate whether a technological system improves their performance and whether it can be used without excessive effort. Systems that are perceived as useful and easy to use are therefore more likely to generate positive attitudes and behavioral intentions.

In healthcare contexts, TAM has been widely applied to explain the adoption of electronic health records, telemedicine platforms, mobile health applications, and clinical decision support systems. Empirical studies consistently confirm that systems perceived as improving efficiency, accuracy, or access to information are more likely to be accepted by both healthcare professionals and patients (Holden and Karsh, 2010; Marangunić and Granić, 2015). TAM's simplicity and clarity have contributed to its continued relevance as a baseline model in digital health research.

However, scholars have also highlighted important limitations of TAM when applied to artificial intelligence. AI systems are often opaque, adaptive, and probabilistic, which complicates users' ability to evaluate usefulness and ease of use in advance. Moreover, TAM does not explicitly account for trust, perceived risk, or ethical concerns—factors that are particularly salient in healthcare AI applications (Glikson and Woolley, 2020; Jobin et al., 2019).

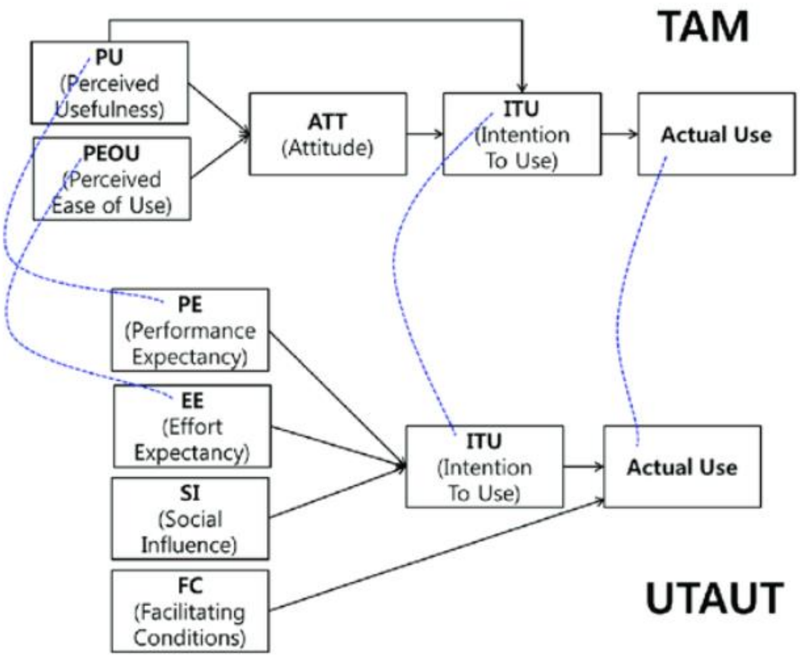
Hungarian TAM-based studies have consistently confirmed the central role of perceived usefulness and perceived ease of use in shaping users' attitudes and behavioral intentions toward digital systems. Research examining the adoption of electronic health services and online health information platforms found that users were more likely to adopt digital solutions when they perceived clear personal benefits, such as improved access to information, time savings, and enhanced convenience (Keszey, 2018; Csiszárik-Kocsir and Garai-Fodor, 2021). These findings align closely with international TAM research and suggest that instrumental evaluations remain a key driver of acceptance in the Hungarian context.

At the same time, several Hungarian studies emphasize that perceived usefulness alone is insufficient to explain acceptance in sensitive domains such as healthcare. Empirical analyses show that trust in institutions, perceived credibility of information sources, and concerns about data security significantly influence attitudes toward digital health technologies (Békésy et al., 2024). These results point to limitations of the original TAM framework and support the need to extend acceptance models when examining AI-based systems that handle health-related information.

3.5.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

To address some of TAM's limitations, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), integrating elements from eight prominent acceptance models. The relationship between TAM and UTAUT is illustrated in Figure 2.

Figure 2: Comparison of the TAM and UTAUT models



Source: Adapted from Kim et al. (2026)

UTAUT identifies four core determinants of behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Table 3 summarizes the conceptual structure of the UTAUT framework. The model explains technology adoptation by identifying the main determinants that influenceusers' behavioral intention and actual system use. Performance expectancy refers to the degree to which individuals believe that using a technological system will improve their performance or provide tangible benefits. Effort expectancy captures the perceived ease associated with using the system, reflecting how simple or complex the technology appears to users. Social influence describes the extent to which individuals perceive that important others expect them to use the technology, while facilitating conditions represent the availability of organizational and technical resources that support system use.

Table 3: Conceptual structure of UTAUT

Core Construct	Definition	Influences
Performance Expectancy	Belief that using the system will provide benefits	Behavioral Intention
Effort Expectancy	Degree of ease associated with system use	Behavioral Intention
Social Influence	Perceived social pressure to use the system	Behavioral Intention
Facilitating Conditions	Perceived organizational and technical support	Use Behavior
Behavioral Intention	Intention to use the technology	Use Behavior
Use Behavior	Actual system usage	Outcome variable

Source: Author's own work based on Venkatesh et al. (2003)

In healthcare research, UTAUT has demonstrated strong explanatory power in studies examining telehealth adoption, patient portals, and digital health services (Venkatesh et al., 2016).

A key innovation of UTAUT is the explicit inclusion of moderating variables such as age, gender, experience, and voluntariness of use, acknowledging that acceptance processes differ across demographic groups (Table 4).

Despite these strengths, UTAUT has been criticized for treating demographic variables primarily as statistical moderators rather than as theoretically meaningful constructs. In the context of artificial intelligence, age and generational background influence not only the strength of acceptance determinants but also trust formation, risk perception, and ethical expectations (Chi et al., 2024; König and Neumayr, 2022). Furthermore, UTAUT—like TAM—does not explicitly model trust or perceived risk as core constructs.

Table 4: Moderating Variables in UTAUT

Moderator	Role
Age	Modifies strength of relationships
Gender	Modifies expectancy effects
Experience	Changes effects over time
Voluntariness of Use	Contextual moderator

Source: Author's own work based on Venkatesh et al. (2003)

UTAUT has also been widely applied in Hungarian research, particularly in studies of e-government services, online public administration, and digital platforms. Hungarian UTAUT-based studies confirm the relevance of performance expectancy, effort expectancy, and social influence in predicting behavioral intention, while also highlighting the importance of facilitating conditions, such as digital infrastructure and institutional support (Keszey and Zsótér, 2020).

In healthcare-related contexts, Hungarian and regional studies applying UTAUT demonstrate that older users tend to place greater emphasis on effort expectancy and facilitating conditions, while younger users focus more strongly on performance expectancy and innovation benefits (Grencíková and Vojtovic, 2017; Nemeth et al., 2022). These findings are particularly relevant for AI acceptance, as conversational AI systems such as ChatGPT may reduce perceived effort while simultaneously raising concerns related to trust and reliability among older populations.

Several Hungarian authors argue that trust should be treated as an independent construct rather than merely an antecedent of perceived usefulness. Studies on digital health information seeking show that users' willingness to rely on algorithmic or automated systems depends strongly on trust in the provider, transparency of the system, and perceived alignment with professional medical standards (Berkup, 2014; Békésy et al., 2024). This mirrors international calls to integrate trust and perceived risk into TAM and UTAUT when applied to AI-driven healthcare technologies.

3.5.3 Extending Acceptance Models: Trust, Risk, Literacy and AI Attitudes

Trust has emerged as a central concept in contemporary AI acceptance research. Trust can be defined as the willingness to rely on a system despite uncertainty about its behavior or outcomes (Glikson and Woolley, 2020). In healthcare, trust is particularly critical because AI-supported decisions may have direct consequences for health and well-being.

Empirical studies show that trust often mediates the relationship between perceived usefulness and behavioral intention, and, in some cases outweighs usefulness in predicting acceptance of AI systems (Kelly et al., 2023; Rodrigues et al., 2024). Closely related is perceived risk, which encompasses concerns about errors, data misuse, bias, and lack of explainability. AI systems described as "black boxes" tend to evoke higher risk perceptions, especially in health-related contexts (Shin, 2021).

CEE and Hungarian studies reinforce these findings. Research among healthcare professionals in Hungary shows positive expectations regarding AI efficiency, alongside strong concerns about data protection, legal responsibility, and ethical accountability (Magyary et al., 2025). Similarly, regional HTA studies highlight transparency and governance as key barriers to trust in AI systems (Tachkov et al., 2022).

An increasingly important factor in AI acceptance is eHealth literacy, defined as individuals' ability to seek, understand, evaluate, and apply electronic health information (Norman and Skinner, 2006). Higher eHealth literacy enables users to critically evaluate digital health content and calibrate trust toward AI systems more appropriately (Diviani et al., 2015; Kim and Xie, 2017).

Conversely, low eHealth literacy may lead either to excessive skepticism toward digital tools or to uncritical reliance on online information. Both patterns may result in problematic outcomes in the context of conversational AI, where fluent responses may mask underlying uncertainty or inaccuracy (Kim and Xie, 2017).

Table 5: Conceptual Dimensions of ehealth Literacy and their relevance to AI-based health communication

Dimension	Definition	Relevance to AI & ChatGPT	References
Functional eHealth Literacy	Ability to read and understand basic online health information	Determines whether users can comprehend AI-generated health content	Norman & Skinner (2006)
Interactive eHealth Literacy	Ability to actively engage with digital health resources	Enables follow-up questioning and dialogic use of ChatGPT	Norman & Skinner (2006); Paige et al. (2018)
Critical eHealth Literacy	Ability to evaluate credibility, accuracy, and relevance of health information	Crucial for identifying AI hallucinations or misleading outputs	Neter & Brainin (2012); Diviani et al. (2015)
Digital Skills	General competence in using digital tools and platforms	Facilitates ease of interaction with conversational AI	van Deursen & van Dijk (2014)
Information Appraisal	Capacity to judge trustworthiness of online sources	Directly linked to trust calibration in AI systems	Kim & Xie (2017)
Health Decision-Making	Applying information to personal health decisions	Influences whether AI outputs are used responsibly	Mackert et al. (2016)

Source: Authors' own work

Table 5 summarizes the main conceptual dimensions of eHealth literacy and highlights their relevance in the context of AI-based health communication. As shown in the table, eHealth literacy is not a single skill but a multidimensional construct that includes functional, interactive, and critical competencies related to accessing, understanding, and evaluating digital health information.

Functional eHealth literacy refers to the ability to read and comprehend basic online health information, which determines whether users are able to understand AI-generated health content. Interactive eHealth literacy extends this capability by enabling users to actively engage with digital health platforms, including the ability to ask follow-up questions and interact with conversational AI systems such as ChatGPT. Critical eHealth literacy represents a higher-level competency that involves evaluating the credibility, accuracy, and relevance of health information. This dimension is particularly important in AI-mediated environments, where users must be able to recognize potential hallucinations or misleading outputs generated by large language models.

Beyond these core components, additional skills such as general digital competence, information appraisal, and health-related decision-making further shape how individuals interpret and apply AI-generated information. Together, these dimensions illustrate that effective engagement with AI-based health communication systems requires not only technical access but also the ability to critically interpret and responsibly apply digital health information. In the context of conversational AI, these competencies influence whether users are able to appropriately evaluate AI-generated responses, calibrate trust in the system, and use the information in a responsible manner when making health-related decisions.

Another important perspective is provided by the Negative Attitudes toward Robots Scale (NARS), originally developed to measure emotional resistance toward robotic systems (Nomura et al., 2006). Although initially designed for physical robots, NARS has increasingly been applied to conversational AI and intelligent systems to capture anxiety, discomfort, and perceived threat associated with autonomous technologies.

Studies conducted in Central and Eastern Europe using NARS or related constructs indicate that negative baseline attitudes toward intelligent systems are associated with lower trust and reduced willingness to engage with AI-based services, particularly among older users and individuals with limited technological experience (Békésy et al., 2024). Incorporating affective resistance into acceptance models therefore provides a more comprehensive understanding of AI adoption processes.

Overall, contemporary research suggests that traditional acceptance models such as TAM and UTAUT remain valuable analytical foundations but require theoretical extensions when applied to AI-based health communication. Integrating constructs such as trust, perceived risk, eHealth literacy, and affective attitudes toward intelligent systems enables a more nuanced understanding of how individuals evaluate and adopt conversational AI technologies in healthcare.

3.6 Demographic Factors in AI Acceptance

Understanding demographic differences in the acceptance of artificial intelligence is essential for interpreting public attitudes toward AI-based health technologies. A growing body of interdisciplinary research suggests that demographic characteristics such as gender, generational background, and educational attainment influence how individuals perceive technological innovations, evaluate potential benefits and risks, and ultimately decide whether to adopt or reject new systems. These differences are particularly relevant in healthcare contexts, where trust, perceived risk, and ethical considerations strongly influence technology acceptance (Kelly et al., 2023; Chi et al., 2024).

3.6.1 Gender Differences in AI Acceptance

Early research on technology acceptance already identified gender as a potentially important factor influencing how individuals evaluate and use information systems. Within the Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use are considered the primary determinants of behavioral intention (Davis, 1989). Empirical studies applying TAM and related models have frequently found that men report higher levels of perceived usefulness and ease of use, while women place greater emphasis on contextual and social considerations (Gefen and Straub, 1997; Venkatesh et al., 2003).

The Unified Theory of Acceptance and Use of Technology (UTAUT) explicitly incorporates gender as a moderating variable, suggesting that social influence and facilitating conditions may play a stronger role for women, particularly in contexts characterized by uncertainty or novelty (Venkatesh et al., 2003; Venkatesh et al., 2016).

Gender differences in technology acceptance are strongly influenced by socialization processes and educational experiences. Research indicates that already during school years, male students tend to engage more frequently with computers and technical subjects, while female students often report lower confidence in their technological abilities, even when objective performance levels are comparable (Cooper, 2006; Kelly et al., 2023).

Trust and risk perception also play a central role in explaining gendered differences in AI acceptance. Artificial intelligence systems are often perceived as complex, opaque, and autonomous, characteristics that can increase uncertainty and perceived risk among users (Glikson and Woolley, 2020; Shin, 2021). Research in risk psychology suggests that women, on average, tend to report higher levels of perceived risk in situations involving uncertainty and potential harm, particularly in domains related to health and safety (Slovic, 1987).

Empirical research focusing specifically on healthcare contexts provides further evidence of gendered differences in AI acceptance. A cross-sectional survey by Fritsch et al. (2022) found that female patients expressed greater reservations about the use of artificial intelligence in medical settings compared to male patients. Women were more likely to emphasize the importance of human oversight, professional accountability, and interpersonal trust, while men more often focused on efficiency and technological performance.

Studies examining conversational AI and ChatGPT show similar patterns. Platt et al. (2024) reported that men were more likely to perceive benefits in using ChatGPT for healthcare-related purposes and to express higher comfort levels with AI-generated health information. Women, in contrast, more frequently raised concerns related to data privacy, misinformation, and the potential misuse of personal health data (Shin, 2021; Slovic, 1987).

While gender differences are evident in many studies, they should not be treated as uniform or static. Intersectional research highlights that gender interacts with age, education, digital literacy, and cultural context in shaping acceptance patterns (Chi et al., 2024; OECD, 2024). For example, younger women with high levels of digital competence may display acceptance patterns similar to those of men, while older men with limited technological experience may express strong skepticism toward AI-based health tools.

Research focusing specifically on Central and Eastern Europe, including Hungary, suggests that gendered patterns of technology acceptance observed internationally are also present in this region, although they may be shaped by distinct historical and institutional factors. Studies examining digital technology adoption in Hungary and neighboring countries indicate that women tend to report lower levels of trust in emerging technologies and higher sensitivity to perceived risks, particularly in domains involving personal data and health-related information (Békésy et al., 2024; Tachkov et al., 2022).

3.6.2 Generational Differences in AI Acceptance

Generational differences in the acceptance and use of artificial intelligence are closely related to patterns of technology socialization over the life course. Technology socialization refers to the process through which individuals acquire skills, attitudes, and expectations toward technological systems through their everyday experiences and historical context.

The concept of generations as socially constructed cohorts is well established in sociological research. Mannheim's (1952) theory of generations emphasizes that individuals who grow up during the same historical period share formative experiences that shape their worldview and behavior. Applied to digital technologies, this perspective suggests that exposure to computers, the internet, and artificial intelligence at different stages of life leads to enduring differences in technological orientation (Berkup, 2014; Grencíková and Vojtovic, 2017).

Older generations, particularly Baby Boomers, were socialized in largely analog environments, where healthcare interactions were predominantly face-to-face and medical authority was rarely questioned. As a result, these cohorts often associate healthcare quality with personal interaction and professional expertise, which can shape their expectations toward digital health solutions (Czaja et al., 2006; Heart and Kalderon, 2013).

Generation X represents a transitional cohort between analog and digital environments. Members of this generation often combine traditional and digital competencies and tend to use digital health tools pragmatically, combining online information seeking with professional consultation (Bol et al., 2018; König and Neumayr, 2022).

Millennials and Generation Z, by contrast, have been socialized in environments where digital technologies are deeply integrated into everyday life. These cohorts generally display higher levels of digital confidence and are more likely to explore new technological solutions, including conversational AI systems such as ChatGPT (Longoni et al., 2019; Nadarzynski et al., 2019).

However, generational differences also appear in levels of trust and risk perception. Older adults tend to rely more strongly on institutional authority and professional endorsement when evaluating technological systems, whereas younger users often base trust on personal experience and perceived system performance (Rodrigues et al., 2024; Shin, 2021).

Research consistently shows that older users report higher levels of perceived risk associated with digital technologies, including artificial intelligence (Czaja et al., 2006; König and Neumayr, 2022). In healthcare contexts, these concerns often relate to data privacy, accountability, and the potential consequences of incorrect information. These differences highlight the importance of tailoring AI communication and governance strategies to the concerns of different generational groups (Table 6).

Table 6: Generational Differences in AI Acceptance and Health-Related Usage

Dimension	Baby Boomers	Generation X	Millennials (Gen Y)	Generation Z	Key References
Technology socialization	Analog upbringing, late digital adoption	Transitional (analog → digital)	Internet-era socialization	Fully digital-native	Mannheim (1952); Berkup (2014); Grencíková & Vojtovic (2017)
Digital health literacy	Lower confidence, strong domain knowledge	Moderate, pragmatic use	High confidence, proactive	High confidence, variable critical skills	Czaja et al. (2006); Neter & Brainin (2012); Békésy et al. (2024)
Trust in AI systems	Institution-based trust	Conditional trust	Experience-based trust	Performance- and value-based trust	Gefen et al. (2003); Rodrigues et al. (2024)
Risk perception	High (safety, accountability)	Moderate	Balanced (risk–benefit)	Lower for low-stakes use	Shin (2021); König & Neumayr (2022)
AI usage in healthcare	Supplementary, low frequency	Preparatory, supportive	Exploratory, self-management	Integrated, first-line information	Bol et al. (2018); Fritsch et al. (2022)
Attitude toward ChatGPT	Cautious, skeptical	Selectively open	Generally positive	Highly open but critical	Platt et al. (2024); Chi et al. (2024)

Source: Author's own collection

In contrast, younger generations are generally more willing to experiment with digital health tools and to balance perceived risks against perceived benefits such as convenience, speed, and accessibility (Bol et al., 2018; Xie, 2009).

3.6.3 Education and AI Acceptance

Educational attainment represents another important determinant of how individuals perceive and adopt artificial intelligence technologies. Education contributes not only to technical skills and digital literacy but also to individuals' ability to critically evaluate technological systems and their potential implications (Chi et al., 2024; Rodrigues et al., 2024). The literature consistently suggests that individuals with higher levels of education are more likely to report positive attitudes toward emerging technologies, including AI-based systems.

One explanation is that education enhances exposure to technology-related knowledge and reduces uncertainty associated with complex systems (Kelly et al., 2023; König and Neumayr, 2022).

Education is also closely linked to digital literacy and eHealth literacy. Individuals with higher educational attainment are generally better able to search for, evaluate, and interpret online health information, which reduces vulnerability to misinformation and improves their ability to critically assess AI-generated content (Neter and Brainin, 2012; Bol et al., 2018).
Empirical research consistently reports a positive association between educational level and acceptance of AI across multiple domains. Large-scale surveys indicate that respondents with tertiary education are more likely to perceive AI as useful, trustworthy, and beneficial compared to those with lower levels of education (Edelman, 2020; Pew Research Center, 2018).

However, higher education does not necessarily eliminate concerns about AI technologies. On the contrary, individuals with greater educational attainment may be more aware of ethical issues such as algorithmic bias, data privacy, and accountability. As a result, their acceptance of AI may be characterized by conditional trust rather than unconditional optimism (Jobin et al., 2019; Shin, 2021).

Conversely, lower educational attainment may be associated with greater uncertainty regarding how AI systems operate, which can increase perceived risk and reduce willingness to engage with digital health technologies (Czaja et al., 2006; van Deursen and van Dijk, 2014).

Conversational AI systems such as ChatGPT introduce additional complexity into this relationship. Natural language interfaces may lower entry barriers and make digital technologies more accessible to users with limited technical expertise. At the same time, fluent AI-generated responses may create an illusion of competence, which can increase the risk of overtrust among users with limited domain knowledge (Liao et al., 2020; Shin, 2021).

Table 7 illustrates how educational attainment influences several key dimensions related to artificial intelligence acceptance in healthcare contexts. As shown in the table, differences in educational level are associated with variations in digital health literacy, trust in AI systems, risk perception, patterns of ChatGPT usage, and ethical awareness. Individuals with lower levels of education often report limited digital health literacy and lower confidence in evaluating online health information. This may lead either to avoidance of AI-based tools or to uncritical reliance on AI-generated information. In contrast, individuals with higher educational attainment tend to demonstrate stronger analytical and evaluative skills, which allow them to interpret digital health content more critically and develop more balanced attitudes toward artificial intelligence.

Table 7: Education and AI Acceptance

Dimension	Lower Education*	Higher Education*	Key References
Digital health literacy	Limited, confidence gaps	High, critical evaluation	Neter & Brainin (2012); Békésy et al. (2024)
Trust in AI	Fragile or overtrust	Conditional, reflective	Shin (2021); Rodrigues et al. (2024)
Risk perception	High uncertainty or misjudgment	Informed risk awareness	Jobin et al. (2019); Longoni et al. (2019)
ChatGPT usage	Avoidance or uncritical reliance	Supplementary, critical use	Bickmore et al. (2018); Liao et al. (2020)
Ethical awareness	Limited articulation	High sensitivity	European Commission (2020)

***** *In this table, lower education refers to individuals whose highest completed level of education is primary, lower secondary, or upper secondary education (ISCED levels 0–3), while higher education refers to individuals with completed tertiary education, including bachelor's, master's, or doctoral degrees (ISCED levels 5–8). (Neter and Brainin, 2012; European Commission, 2020; Békésy et al., 2024).*
Source: Authors own collection

The table also highlights differences in trust and risk perception. Users with lower education levels may experience higher uncertainty when interacting with AI systems, sometimes resulting in fragile trust or overreliance. Highly educated users, however, are more likely to exhibit conditional and reflective trust, recognizing both the benefits and limitations of AI-based systems. This often leads to a more critical and supplementary use of conversational AI tools such as ChatGPT rather than complete reliance on automated responses.

Overall, the comparison presented in Table 7 suggests that educational attainment plays a significant role in shaping how individuals interpret, evaluate, and apply AI-generated health information. Higher education is generally associated with stronger digital competencies and greater ethical awareness, which may support more informed and responsible engagement with AI-based health communication technologies.

Evidence from Hungary and the broader Central and Eastern European region further supports the role of education in shaping AI acceptance. Hungarian studies indicate that educational attainment is one of the strongest predictors of digital health literacy and trust in online health information sources (Békésy et al., 2024).

4. HYPOTHESES OF THE DISSERTATION

Building on the reviewed literature, it becomes evident that acceptance of artificial intelligence in health-related contexts is shaped by a complex interplay of individual characteristics, cognitive evaluations, and social factors. Attitudes toward AI are not determined solely by technical performance or functional benefits but are deeply influenced by demographic background, levels of trust, perceived risks, and the broader socio-cultural environment in which technology is embedded.

The literature reviewed in the previous chapters indicates that trust, perceived risk, and ethical concerns play a fundamental role in shaping users' attitudes toward AI-based health communication systems. At the same time, classical technology acceptance models such as TAM and UTAUT highlight the importance of perceived usefulness, ease of use, and social influence in determining behavioral intention. Contemporary research increasingly suggests that these models should be complemented by additional factors, including trust formation, eHealth literacy, and affective attitudes toward intelligent systems.

In the context of conversational AI systems such as ChatGPT, these dimensions become particularly relevant because such systems operate at the intersection of digital information provision and health-related advisory communication. Users must therefore evaluate not only the functional usefulness of these systems but also their reliability, trustworthiness, and ethical legitimacy.

Demographic characteristics further shape how individuals interpret and evaluate AI-based health technologies. Previous research indicates that age, gender, and educational background influence digital literacy, risk perception, and trust formation, which in turn affect attitudes toward AI adoption. Younger individuals and users with higher levels of digital competence tend to display greater openness toward emerging technologies, while older users or individuals with lower levels of technological familiarity may express stronger concerns regarding reliability, privacy, and accountability (König and Neumayr, 2022; Chi et al., 2024).

In addition, education plays an important role in shaping how individuals interpret and evaluate AI-generated information. Higher educational attainment is generally associated with stronger analytical skills, higher digital literacy, and a greater ability to critically assess technological systems. As a result, highly educated users may display a form of conditional acceptance toward AI technologies, recognizing both their potential benefits and their limitations (Shin, 2021; Liao et al., 2020).

Based on the theoretical perspectives discussed in the literature review, it can be assumed that demographic characteristics interact with trust-related perceptions and technological evaluations in shaping attitudes toward conversational AI systems used for health-related purposes. On this basis, the following hypotheses are formulated:

Hypothesis 1 (H1): Younger individuals demonstrate higher levels of acceptance and trust toward ChatGPT for health-related use than older individuals (Prensky, 2001; Cecconi et al., 2025).

Hypothesis 2 (H2): Demographic characteristics significantly influence acceptance of ChatGPT, although their effects differ in strength across variables (König and Neumayr, 2022).

Hypothesis 3 (H3): Higher levels of trust in ChatGPT are positively associated with perceived usefulness and intention to use (Rodrigues et al., 2024; Tan and Ong, 2024).

Hypothesis 4 (H4): Demographic characteristics moderate the relationship between perceived usefulness and behavioral intention, in line with the UTAUT framework (Venkatesh et al., 2003).

Hypothesis 5 (H5): Higher levels of educational attainment are associated with more informed and conditional acceptance of ChatGPT in health-related contexts, characterized by higher perceived usefulness combined with greater sensitivity to ethical and accuracy-related concerns (Shin, 2021; Liao et al., 2020).

5. METHODOLOGY

This chapter outlines the methodological approach applied in the dissertation. The structure follows the chronological order of the research process, beginning with the secondary data analysis, followed by the complementary empirical dataset, and then the primary survey. The chapter concludes with the description of the analytical methods and the role of AI-based language support.

5.1 Secondary Data Collection

In addition to primary data collection, the dissertation includes a systematic secondary data analysis to provide a broader context for interpreting attitudes toward ChatGPT in health-related information use.

The secondary analysis serves three main purposes. First, it offers a macro-level overview of digital health information use, digital skills, and trust-related indicators across demographic groups. Second, it allows comparison between population-level patterns and the results of the empirical surveys. Third, it supports the evaluation of whether the hypotheses formulated in the dissertation align with broader statistical trends.

Secondary data were collected from internationally recognized statistical sources, including:

- **Eurostat (European Commission)** for digital skills and health-related internet use
- **Eurobarometer** for trust, risk perception, and attitudes toward digital health
- **Hungarian Central Statistical Office (KSH)**
- **Organisation for Economic Co-operation and Development (OECD)** for digital health readiness and AI-related concerns

These sources were selected for several reasons. They provide regularly updated and publicly accessible datasets, transparent methodological documentation, and detailed demographic breakdowns relevant to the research. In addition, they include indicators related to digital health usage, digital skills, and information-seeking behaviour.

Although these datasets do not measure attitudes toward ChatGPT directly, they capture closely related variables such as:

- online health information seeking,
- use of digital health services,

- digital literacy,
- education-related inequalities,
- age-related differences in digital engagement.

These variables are consistent with the theoretical framework of the study, particularly the constructs derived from TAM, UTAUT, and trust-based extensions. As a result, the secondary analysis provides an important contextual background for interpreting the empirical findings.

Beyond providing contextual background, the secondary data also serve as a reference point for interpreting the empirical findings of the primary and complementary datasets. Although direct comparison is not always possible due to differences in measurement, the secondary indicators help to identify whether observed patterns—such as age-related differences in digital engagement or variations in trust—are consistent with broader population-level trends. In this sense, the secondary analysis supports the triangulation of results and strengthens the overall interpretability of the study.

5.2 Complementary Dataset: Representative Survey among Adults Aged 40 and Above

To complement the secondary analysis, an additional empirical dataset was included to examine attitudes toward ChatGPT among older age groups. This dataset is treated as a separate study and not as a direct extension of the primary sample.

Data were collected in May 2024 through a cross-sectional online survey among 200 Hungarian individuals aged 40 years and above. Quota sampling ensured representativeness based on age, gender, and place of residence, using the 2011 Hungarian census as a reference. Data collection was carried out by a professional market research company using email-based invitations. Participation was voluntary, anonymous, and fully compliant with data protection regulations, and only fully completed questionnaires were included in the analysis. Participation was voluntary and anonymous. The sample covered respondents aged 40–82 years, with balanced gender distribution and a diverse educational background.

Table 8: Demographic variables of the representative 40+ sample (N=200, %)

Sociodemographic variables	Category	N	%
Total sample		200	100.0
Gender	Male	101	50.5
	Female	99	49.5
Generation	Millennials	20	10.0
	Generation X	104	52.0
	Baby boomers	75	37.5
	Silent Generation	1	0.5
Education	Max. 8 years	8	4.0
	Vocational	40	20.0
	High school	92	46.0
	Degree	60	30.0

Source: Author's own data collection

The sample consisted of respondents aged 40–82 years, with a balanced gender distribution (50.5% male, 49.5% female). In terms of generational composition, 52% belonged to Generation X, 37.5% to the Baby Boomer cohort, and 10% to older Millennials, while the Silent Generation was excluded from further analysis due to insufficient sample size. Educational attainment varied, with 30% holding a higher education degree, 46% having completed secondary education, and 4% reporting fewer than eight years of formal schooling (Table 8).

The survey focused specifically on five items assessing attitudes toward the health-related use of ChatGPT, all of which were conceptually derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Responses were recorded on a four-point forced-choice scale, deliberately excluding a neutral midpoint in order to elicit clear directional attitudes. Descriptive statistics and inferential analyses (ANOVA and linear regression) were conducted using Microsoft Excel and SPSS 16.0.

5.3 Primary Data Collection

The primary empirical study was designed to examine attitudes toward ChatGPT in healthcare among younger, digitally active respondents, with a particular focus on trust, perceived usefulness, and behavioural intention.

Data were collected through a cross-sectional online survey conducted between November 2024 and May 2025 using Google Forms. Participation was voluntary and anonymous and all respondents provided informed consent prior to participation. 172 fully completed responses were included in the analysis. The survey was administered in Hungarian, and the full questionnaire is provided in Appendix II.

The questionnaire aimed to capture:

– trust in AI-based health communication,
– perceived usefulness and behavioural intention,
– health information-seeking behaviour,
– expectations regarding the role of ChatGPT in healthcare,
– the relationship between digital health literacy and AI acceptance.

To ensure theoretical consistency, the questionnaire combined validated scales with self-developed items derived from TAM and UTAUT.

The eHEALS scale measured digital health literacy (8–40 points), while the NARS scale captured negative attitudes toward AI (14–70 points). These instruments made it possible to distinguish between informed acceptance and acceptance driven by uncertainty or overconfidence.

Two additional item blocks were included:

– an 8-item scale on AI/robot attitudes in healthcare,
– a 5-item ChatGPT-specific module.

5.3.1 Background Variables

After presenting the measurement instruments, the background variables used in the analysis are introduced. The sample is strongly skewed toward younger respondents: 90.7% belong to Generation Z with 51.7% aged 18–21 years and 39.0% aged 22–28 years. Millennials accounted for 8.7%, while only one respondent (0.6%) belonged to Generation X. The gender distribution is balanced, 55.8% of respondents were female (n = 96) and 44.2% male (n = 76) (Table 9). While this composition limits generalizability to the full Hungarian population, it provides analytically valuable insight into cohorts that are among the earliest and most intensive users of conversational AI technologies. This cohort-specific focus is particularly relevant for examining Hypothesis 1, which assumes generational differences in AI acceptance and trust.

Table 9: Demographic variables of student sample (N=172, %)

Sociodemographic variables		Total sample	
		N	%
Total sample		172	100.0
Gender	Male	76	44.2
	Female	96	55.8
Age	18-21 years (Gen Z)	89	51.7
	22 - 28 years (Gen Z)	67	39.0
	29 - 44 years (Millennials)	15	8.7
	45+ years (Gen X)	1	0.6
Place of residence	Capital city	56	32.6
	City with county rights	32	18.6
	Other town	46	26.7
	Other settlement	38	22.1
Employment/Study status	Employed*	22	12.8
	Student	91	52.9
	Both *	56	32.6
	Other**	3	1.7
Relative income	Regular financial difficulties	1	0.6
	Sometimes insufficient for basic needs	4	2.3
	Sufficient but unable to save	27	15.7
	Able to live on it with limited savings	82	47.7
	Very good financial situation with ability to save	42	24.4
	Prefer not to answer	16	9.3
Highest completed education	Primary school (max. 8 years)	4	2.3
	Vocational school	0	0.0
	Secondary vocational school	7	4.1
	High school diploma	126	73.3
	Higher education degree	35	20.3
Ongoing studies	Higher-level vocational training	34	19.8
	Bachelor's programme	117	68
	Master's programme	16	9.3
	Undivided programme (BA/BSc+MA/MSc)	1	0.6
	PhD	4	2.3

**Respondents employed at the time of the survey.*
***Special circumstances e.i. childcare responsibilities*
Source: Author's own data collection

Educational attainment within the sample was relatively high, reflecting the study's focus on digitally active populations. 73.3% of respondents held a high school diploma, while 20.3% already possessed a higher education degree. At the time of data collection, 68.0% were enrolled in a bachelor's programme, 9.3% in a master's programme, and 2.3% were PhD students. This educational profile provides a suitable basis for examining how education and digital health literacy relate to attitudes toward ChatGPT, supporting the empirical testing of Hypothesis 2 and the education-related aspects of Hypothesis 3.

A central methodological strength of the study lies in the theoretically grounded construction of the questionnaire. The instrument integrates two validated scales—the eHealth Literacy Scale (eHEALS) and the Negative Attitudes toward Robots Scale (NARS)—with self-developed items derived explicitly from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). This integration ensures that abstract theoretical constructs such as perceived usefulness, effort expectancy, trust, and behavioral intention are consistently translated into measurable variables.

The eHEALS was used to assess respondents' perceived skills in finding, evaluating, and applying online health information. The scale consists of 8 items rated on a five-point Likert scale (1=totally disagree, 5=totally agree), yielding scores between 8 and 40, with higher values indicating higher perceived digital health literacy. Including this scale enables the study to distinguish between acceptance based on informed evaluation and acceptance potentially driven by overconfidence or limited understanding. This distinction is crucial for interpreting the relationship between trust and intention to use ChatGPT, as proposed in Hypothesis 3.

The NARS scale complements this approach by capturing emotional, cognitive, and social dimensions of resistance toward robots and AI. Scores range from 14 to 70, with higher values indicating more negative attitudes. Although no validated Hungarian version of NARS exists, a carefully translated version was applied consistently across the sample. This instrument allows the analysis to account for underlying discomfort and anxiety that may not be captured by utility-based acceptance models alone, thereby strengthening the examination of demographic differences assumed in Hypotheses 1 and 2.

In addition to standardized scales, two self-developed item sets were included. The first consisted of eight items assessing attitudes toward robots and AI in medical contexts, with total scores ranging from 8 to 40. These items were explicitly mapped onto UTAUT constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) and NARS subscales, ensuring conceptual coherence.

It is important to emphasize that the results of the primary survey are not generalizable to the Hungarian population, as the sample is not representative in terms of key demographic characteristics. The findings therefore apply strictly to the analysed sample. At the same time, the dataset provides meaningful and directionally relevant insights, particularly regarding younger users who are among the earliest adopters of conversational AI.

Table 10: 8-item self-developed questionnaire on attitudes toward robots and Artificial Intelligence in medical contextson

Statement	UTAUT Construct	NARS Subscale	Justification
1. I would have no problem discussing medical issues with robots or artificial intelligence.	Effort Expectancy (EE)	S1 – Negative attitudes toward situations of interaction with robots	Indicates perceived ease and comfort in interacting with AI/robots in healthcare, suggesting low interaction-related anxiety.
2. I trust doctors more than robots or artificial intelligence.	Performance Expectancy (PE) / Trust	S2 – Negative attitudes toward the social influence of robots	Reflects comparative trust in human providers over AI, tied to perceived capability and social role.
3. I would feel nervous discussing my medical condition with a robot.	Effort Expectancy (EE)	S1 – Negative attitudes toward situations of interaction with robots	Captures emotional discomfort and anticipated difficulty in direct health-related interaction with robots.
4. I would not mind if robots or AI made decisions in medical matters.	Performance Expectancy (PE)	S2 – Negative attitudes toward the social influence of robots	Suggests acceptance of AI/robot decision-making, indicating lower concern over their societal role in healthcare.
5. I would not mind showing a part of my body to a robot for medical examination purposes.	Effort Expectancy (EE)	S1 – Negative attitudes toward situations of interaction with robots	Reflects willingness to engage in physically intimate medical interactions with robots, indicating low perceived barriers.
6. I think medicine is already highly dependent on robots.	Social Influence (SI)	S2 – Negative attitudes toward the social influence of robots	Expresses perception of current technological integration in medicine, shaped by societal observation and norms.
7. I am not bothered by the increasing use of AI and robots in medicine.	Social Influence (SI) / Performance Expectancy (PE)	S2 – Negative attitudes toward the social influence of robots	Indicates acceptance of growing AI/robot adoption, influenced by societal attitudes and perceived benefits.
8. I feel that in the future robots and AI will dominate healthcare.	Facilitating Conditions (FC)	S2 – Negative attitudes toward the social influence of robots	Reflects expectation of future widespread integration, assuming infrastructure and societal readiness.

Source: Author own work

The second set comprised five ChatGPT-specific items, also rated on a five-point Likert scale (1=totally disagree, 5=totally agree), designed to assess trust, health information–seeking behavior, and expectations regarding future integration of ChatGPT into healthcare. These items operationalize UTAUT constructs directly and provide the empirical basis for testing Hypothesis 4, which assumes moderation effects in line with the UTAUT framework (Table 10).

Table 11: 5-item self-developed questionnaire about the use of chatgpt in healthcare

Statement	Mapped UTAUT Construct	Justification
1. I consider ChatGPT to be a reliable source for questions about my medical and health conditions.	Performance Expectancy (PE)	Reflects the belief that ChatGPT effectively supports health-related tasks by providing reliable information.
2. In my opinion, the usage of ChatGPT has a positive impact on the health literacy of society.	Social Influence (SI)	Indicated the perceptions that ChatGPT benefits society at large, shaping attitudes through perceived collective usefulness
3. I ask health questions to ChatGPT more often than to a doctor.	Facilitating Conditions (FC)	Suggests that ChatGPT1s availability, convenience, and accessibility enable its frequent use over traditional consultation
4. I would rather go to ChatGPT with uncomfortable, overly personal questions than see a doctor in person.	Effort Expectancy (EE) (with elements of PE)	Shows comfort in using ChatGPT for sensitive topics, reducing effort and emotion barriers, while also implying trust in its usefulness
5. I believe that ChatGPT will soon be part of everyday healthcare.	Facilitating Conditions (FC)	Reflects expectations of future integration into healthcare systems, assuming supportive infrastructure and institutional adaptation.

Source: Author own work

The relatively homogeneous structure of the sample has important implications for interpretation. On the one hand, it allows for a focused analysis of attitudes within a digitally experienced and education-oriented population. On the other hand, it limits the extent to which differences across age and socioeconomic strata can be observed. The findings should therefore be interpreted as reflecting early-stage attitudes toward AI in healthcare among younger, educated users, rather than as representative of the population as a whole.

At the same time, this group is particularly relevant for understanding emerging patterns of technology acceptance. As frequent users of digital tools and information sources, university students are often among the first to encounter and experiment with new technologies such as conversational AI. Their attitudes may therefore provide early indications of broader adoption trends.

The key methodological and structural differences between the two empirical datasets (primary data and complementary dataset) are summarised in Table 12. The comparison highlights that the two datasets differ not only in sampling strategy and demographic composition, but also in their analytical role within the study.

Table 12: Overview of the Two Empirical Data Collections Used in the Study

Dimension	Primary dataset (University-based survey)	Complementary dataset (Representative 40+ survey)
Purpose of data collection	Primary empirical investigation of attitudes toward ChatGPT in healthcare	Validation and contextual extension of generational findings
Time of data collection	Nov 2024 – May 2025	May 2024
Sample size (N)	172	200
Target population	Hungarian university students (18+)	Hungarian adults aged 40+
Sampling strategy	Convenience sampling	Quota sampling (census-based)
Representativeness	Not representative	Representative by age, gender, residence
Main theoretical framework	TAM, UTAUT, trust- and risk-based extensions	UTAUT
ChatGPT-related items	5-item ChatGPT module (final block of questionnaire)	Same 5 ChatGPT items, unchanged in content
Conceptual equivalence	Original item set	Identical wording and construct mapping
UTAUT constructs measured	PE, EE, SI, FC	PE, EE, SI, FC
Response scale	5-point Likert scale	4-point forced-choice Likert scale
Reason for scale choice	Allows neutrality and gradation in exploratory research	Forces directional judgment in short representative survey
Analytical role	Core hypothesis testing	Independent supportive evidence (no direct statistical comparison)

Source: Author's own work

In addition to its descriptive value, the complementary dataset plays an important interpretative role in relation to the primary survey. While the two datasets are not directly comparable due to differences in sampling strategy and measurement scales, they reveal consistent structural patterns. In both datasets, acceptance of ChatGPT in healthcare appears to be conditional and strongly dependent on the perceived role of the technology.

At the same time, notable differences emerge across age groups. The primary dataset, dominated by younger respondents, reflects more exploratory and ambivalent attitudes, whereas the representative 40+ dataset shows more clearly articulated boundaries regarding trust, responsibility, and the limits of AI in healthcare. This contrast supports the interpretation that acceptance is shaped not only by digital familiarity, but also by life-stage experiences and expectations related to healthcare systems.

The combined use of secondary data, the representative 40+ survey, and the primary dataset enables a triangulated analytical approach. Rather than relying on a single source of evidence, the study integrates macro-level indicators, representative population data, and micro-level attitudinal responses.

This triangulation makes it possible to identify patterns that are consistent across datasets, such as limited trust in AI-based health communication and the rejection of substituting healthcare professionals with AI. At the same time, it allows for the identification of differences that are specific to particular groups, especially across age cohorts.

Importantly, the primary dataset provides detailed attitudinal insights, while the complementary dataset offers population-level validation, and the secondary data situate these findings within broader structural trends. Together, these layers strengthen the interpretability of the results and reduce the risk of drawing conclusions based on sample-specific effects alone.

5.4 Data Analysis

Data analysis combined descriptive statistics, analysis of variance (ANOVA), and linear regression. Descriptive statistics were used to summarize central tendencies and dispersion, while ANOVA tested group differences across demographic variables with a significance level set at $p < 0.05$. Linear regression analysis was applied to examine relationships between trust, perceived usefulness, and behavioral intention, with the coefficient of determination (R^2) used to assess explanatory power. Analyses were conducted using Microsoft Excel and SPSS 16.0, allowing both accessibility and methodological rigor.

Taken together, the methodological design provides a coherent and empirically grounded framework for testing the proposed hypotheses. The explicit integration of TAM and UTAUT into the questionnaire, the use of validated scales, and the detailed demographic profiling of the sample ensure that Hypotheses 1–4 are not merely theoretical propositions but are directly linked to measurable variables. While the sample composition necessitates cautious generalization, the inclusion of concrete demographic, educational, and literacy-related indicators allows for a nuanced and transparent interpretation of acceptance patterns toward ChatGPT in health-related contexts.

Overall, the methodological approach ensures a clear connection between the theoretical framework, the empirical data, and the tested hypotheses. Although the primary sample does not allow statistical generalization, the combination of different data sources supports a nuanced and well-grounded interpretation of the results.

5.5 Use of AI-Based Language Support

To improve linguistic clarity and academic style, ChatGPT was used exclusively as a language support tool. Its role was limited to grammar checking and wording refinement. ChatGPT did not contribute to the research design, data collection, analysis, or interpretation of results. All scientific decisions and conclusions remain the sole responsibility of the author.

6. RESULTS

This chapter presents the empirical findings of the dissertation based on a primary survey conducted among Hungarian university students (N = 172), complemented by a representative dataset of individuals aged 40 and above, as well as secondary statistical indicators used for contextual interpretation. The results are organized along thematic lines, focusing on digital health literacy, general attitudes toward artificial intelligence and robotics in healthcare, and perceptions of ChatGPT in health-related contexts.

6.1 Descriptive Statistics of the Main Constructs

Four composite measures were used in the primary survey: digital health literacy (eHEALS), negative attitudes toward robots (NARS), an 8-item scale capturing general attitudes toward AI and robotics in healthcare, and a 5-item scale assessing perceptions of ChatGPT in health-related contexts. Each scale was constructed as the sum of item responses, with higher values indicating stronger endorsement of the underlying construct (Table 13).

Table 13: Descriptive statistics of the main variables (N = 172)

Measure (sum score)	Theoretical range	Mean	SD
eHEALS (8 items)	8–40	28.69	5.45
NARS (14 items)	14–70	42.18	7.07
robots/AI (8 items)	8–40	25.19	3.25
ChatGPT (5 items)	5–25	12.77	3.94

Source: Author's own calculation based on the primary survey dataset

The mean eHEALS score was 28.69 (SD = 5.45) on a scale ranging from 8 to 40. This suggests a relatively high level of perceived competence in searching for, evaluating, and using online health information. Given the characteristics of the sample, this result is not surprising; university students are typically frequent users of digital information sources and are accustomed to navigating online environments.

Negative attitudes toward robots, measured by NARS, yielded a mean score of 42.18 (SD = 7.07) on a scale of 14 to 70. This indicates a moderate level of reservation toward automation and robotics. Importantly, the relatively high standard deviation points to noticeable differences within the sample: while some respondents are clearly comfortable with automation, others remain more cautious or skeptical.

The 8-item healthcare-focused attitude scale produced a mean score of 25.19 (SD = 3.25), suggesting a middle-ground position toward AI and robotics in healthcare. This scale includes both positively and negatively framed items; therefore, the result should not be interpreted as straightforward acceptance but rather as an overall orientation that combines openness with caution.

Finally, the ChatGPT-related scale showed a mean of 12.77 (SD = 3.94) on a 5–25 range. This places attitudes toward ChatGPT below the midpoint of the scale, indicating cautious openness rather than strong endorsement. Compared to the other constructs, this domain shows greater variability, which suggests that conversational AI elicits more mixed and less settled reactions than general AI or robotics.To better understand variability across constructs, relative dispersion was also calculated.

Table 14: Relative variability of the main constructs (Coefficient of Variation,%,N=172)

Measure	Mean	SD	CV (%)
eHEALS	28.69	5.45	19.0
NARS	42.18	7.07	16.8
robots/AI	25.19	3.25	12.9
ChatGPT	12.77	3.94	30.9

Source: Author's own calculation based on the primary survey dataset

To complement the interpretation of standard deviations, the coefficient of variation (CV) was calculated for each construct (Table 14). While standard deviation reflects absolute dispersion, the CV expresses variability relative to the mean, allowing for a more meaningful comparison across scales with different ranges.

The results reveal clear differences in response consistency across the four constructs. The 8-item healthcare AI scale shows the lowest relative variability (CV = 12.9%), indicating that respondents' attitudes toward AI and robotics in healthcare are relatively stable and internally consistent. A similar, though slightly higher level of consistency is observed for NARS (CV = 16.8%) and eHEALS (CV = 19.0%), suggesting that both negative attitudes toward robots and perceived digital health literacy are fairly homogeneous within the sample.

In contrast, the ChatGPT-related scale displays substantially higher relative variability (CV = 30.9%). This indicates that respondents' opinions about ChatGPT in healthcare are considerably more dispersed. In practical terms, while some participants are relatively open to using ChatGPT in health-related contexts, others remain clearly skeptical. This divergence is not as pronounced in the other constructs.

This pattern suggests that attitudes toward ChatGPT are less consolidated and more uncertain than general attitudes toward AI or digital competence. Unlike digital health literacy—which is likely shaped by accumulated experience—and general AI attitudes—which may reflect broader cultural narratives, perceptions of ChatGPT appear to be more situational and still in formation. The higher variability therefore reflects not only disagreement but also the absence of a widely shared, stable evaluation framework.

From an analytical perspective, this finding supports the decision to examine ChatGPT attitudes at the item level in subsequent sections. Aggregated scores alone may obscure important differences in how respondents evaluate specific aspects of conversational AI in healthcare. A comparison with theoretical midpoints further refines the interpretation. While digital health literacy is clearly above the midpoint, attitudes toward ChatGPT fall below it. This indicates that respondents are not merely cautious but tend toward a more skeptical evaluation of conversational AI in healthcare contexts.

An important insight emerges when the four constructs are considered together rather than separately. While digital health literacy reaches the highest level, attitudes toward ChatGPT remain the lowest. This divergence suggests that respondents do not evaluate all digital health-related constructs in the same way.

One possible explanation is that digital health literacy reflects accumulated experience with relatively familiar tools, such as search engines and health websites. In contrast, ChatGPT represents a newer and less established technology, which may trigger greater uncertainty.

This contrast highlights a structural difference between competence and trust. While respondents feel confident in their ability to navigate digital information environments, they remain cautious when evaluating the reliability of AI-generated content. This suggests that trust is not simply a function of competence, but is shaped by additional factors such as perceived risk, accountability, and the perceived legitimacy of the source.

This pattern reveals an internal inconsistency in the data. While respondents express relatively positive attitudes toward AI in general, their evaluation of ChatGPT remains significantly more cautious. This suggests that respondents apply different evaluative criteria to abstract technologies and concrete applications, with the latter being judged more critically.

Table 15: Competence–Trust Gap (standardized values, %, N=172)

Construct	Standardized
eHEALS	72
ChatGPT	51
Difference	-21

Source: Author's own calculation based on the primary survey dataset

This gap can be quantified by comparing standardized values (Table 15). While digital health literacy reaches approximately 72% of its maximum, ChatGPT attitudes reach only 51%, resulting in a difference of more than 20 percentage points. This substantial gap indicates that competence does not translate directly into trust. Even respondents who feel confident in navigating digital health information remain cautious when evaluating AI-generated content.

6.2 Digital Health Literacy and Information Competence

Digital health literacy plays a central role in shaping how individuals engage with online health information and, by extension, AI-based tools. In this sample, the overall level of digital health literacy was relatively high, which aligns with expectations for a university population.

Table 16 summarizes the digital health literacy results of the sample. When examining group differences, only modest variation emerges. Women reported slightly higher eHEALS scores than men (29.08 vs. 28.18), but the difference was not statistically significant. Similarly, older respondents (29–44 years) tended to report somewhat higher digital health literacy than younger participants, although this difference also remained non-significant.

More pronounced differences appear in relation to education. Respondents with a university degree scored significantly higher on eHEALS than those with only a high school diploma (30.74 vs. 28.16, $p < 0.05$). A similar pattern can be observed when comparing students at different stages of their studies: those enrolled in MA/MSc programmes reported higher scores than those at BA/BSc level. These findings are consistent with the idea that education enhances not only actual skills but also confidence in handling information. At the same time, it is worth noting that high perceived competence does not necessarily translate into higher trust in AI-based tools, a point that becomes more evident in later sections.

Income and place of residence showed only minor descriptive differences and did not reach statistical significance. This suggests that, within this relatively homogeneous sample, digital health literacy is influenced more strongly by educational factors than by socioeconomic variation.

Table 16: eHEALS across sociodemographic groups (N=172)

Group	N	Mean (eHEALS)	SD
Gender			
Female	96	29.08	5.52
Male	76	28.18	5.37
Age			
18-28	156	28.42	5.42
29-44	15	31.07	5.48
Residence			
City	88	28.86	5.57
Town/Village	84	28.50	5.37
Education			
Max high school	137	28.16	5.39
University degree	35	30.74	5.33
Ongoing studies			
BA/BSc or lower	151	28.33	5.43
MA/MSc or higher	21	31.24	5.08

Source: Author's own calculation based on the primary survey dataset

Table 17 provides a more detailed overview of statistical significance across sociodemographic variables. The results confirm that education is the only consistent factor influencing digital health literacy. Both highest completed education and current level of studies show statistically significant differences, while gender, age, income, and place of residence do not.

Table 17: Statistical significance of group differences in digital health literacy (eHEALS) (N=172)

Grouping variable	Test	p-value	Interpretation
Gender	t-test	0.283	ns
Age	t-test	0.161	ns
Residence	t-test	0.663	ns
Relative income	ANOVA	0.247	ns
Highest completed education	t-test	0.014	*
Ongoing studies	t-test	0.022	*

Tests: t-test for two-group comparisons; one-way ANOVA for income groups.
Interpretation: ns = not significant ($p > 0.05$)
$p < 0.05$ significant ($p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)*
Source: Author's own calculation based on the primary survey dataset

This pattern suggests that perceived competence in handling online health information is primarily shaped by educational experience rather than broader sociodemographic background. At the same time, the lack of significant differences across most variables indicates a relatively homogeneous level of digital health literacy within the sample.

A more detailed picture emerges when examining the individual items of the eHEALS scale (Table 18). While respondents report high confidence in locating and using online health information, lower scores are observed for items related to critical evaluation and decision-making.

Table 18: Item-level analysis of eHEALS (N = 172)

Item (in short)	**Mean**	**SD**
Finding health resources	3.8	0.9
Using online health info	3.7	0.8
Evaluating information quality	3.5	1.0
Confidence in using info	3.9	0.9
Identifying reliable sources	3.4	1.1
Applying information	3.6	0.9
Understanding information	3.7	0.8
Decision-making confidence	3.3	1.1

Source: Author's own calculation based on the primary survey dataset (N = 172).

This suggests that digital health literacy in the sample is stronger in terms of access and usage than in terms of critical assessment. In other words, respondents feel capable of finding information, but are less confident in judging its reliability.

A further aspect worth considering is the potential discrepancy between perceived and actual competence. High eHEALS scores indicate confidence, but do not necessarily guarantee the ability to critically evaluate complex or misleading information. This issue becomes particularly relevant in the context of AI-generated content. Unlike traditional sources, conversational AI systems produce responses that appear coherent and authoritative, even when they may contain inaccuracies. As a result, users with high confidence in their digital skills may be more vulnerable to accepting such outputs without sufficient verification. This introduces a paradox: higher digital literacy may increase engagement with AI tools, while not necessarily reducing the risk of misinformation. In this sense, digital competence may act as both an enabling and a risk factor.The results therefore point to a structural gap between competence and trust. While respondents feel capable of navigating digital health information, this does not translate into confidence in AI-generated outputs. This gap represents a potential barrier to adoption, as the ability to use a system does not necessarily imply willingness to rely on it.

6.3 General Attitudes Toward AI and Emotional Responses to Automation

Attitudes toward AI in healthcare are shaped not only by perceived usefulness but also by emotional responses to automation. In this study, these dimensions were captured through NARS and the 8-item healthcare-focused scale.

Table 19: NARS across sociodemographic groups (N=172, mean, SD)

Group	N	Mean (NARS)	SD
Gender			
Female	96	43.01	6.31
Male	76	41.12	7.85
Age			
18-28	156	42.51	7.21
29-44	15	39.07	4.67
Residence			
City	88	41.82	6.87
Town/Village	84	42.55	7.31
Income			
Able to save	124	42.00	6.93
Financial difficulties	5	46.40	17.05
Limited income	27	41.44	5.07
Education			
Max high school	137	42.94	7.24
University degree	35	39.17	5.52
Ongoing studies			
BA/BSc or lower	151	42.62	7.04
MA/MSc or higher	21	38.95	6.62

Source: Author's own calculation based on the primary survey dataset (N = 172).

Overall, respondents displayed moderate levels of negative attitudes toward robots. While the average score does not indicate strong resistance, it does point to the presence of underlying concerns. The variability of responses suggests that these concerns are not evenly distributed: some respondents are clearly more comfortable with automation than others. The distribution of negative attitudes toward robots (NARS) across sociodemographic groups is presented in Table 19. Overall, the results indicate moderate levels of negative attitudes, with some variation across groups.

Table 20: Statistical significance of group differences in NARS and the 8-item AI attitude scale (N=172)

Grouping variable	NARS p-value	8-item AI scale p-value	Main interpretation
Gender	0.090	0.038	Gender effect only for AI scale
Age	0.078	0.313	Not significant
Residence	0.501	0.085	Not significant
Relative income	0.451	0.051	Weak/borderline effect
Highest completed education	0.001	0.262	Strong effect on NARS only
Ongoing studies	0.026	0.212	Affects NARS only

Tests: t-test for two-group comparisons; one-way ANOVA for income groups.
Interpretation: ns = not significant ($p > 0.05$)
$p < 0.05$ significant ($p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)*
Source: Author's own calculation based on the primary survey dataset (N = 172).

Table 20 highlights an important distinction between general emotional attitudes toward robots and more context-specific evaluations of AI in healthcare. Education shows a strong and consistent effect on NARS, indicating that higher educational attainment is associated with lower emotional resistance to automation. However, this effect does not extend to the healthcare-specific AI scale.

In contrast, gender differences appear only in the 8-item healthcare AI scale, but not in NARS. This suggests that demographic influences depend on the level of abstraction: general emotional attitudes are shaped primarily by education, while context-specific evaluations are more sensitive to gender-related differencesOverall, these results support the interpretation that attitudes toward AI are multidimensional, and that different factors influence general perceptions and concrete applicationsGender differences in NARS were small and not statistically significant, although women reported slightly higher levels of negative attitudes. In contrast, the 8-item healthcare AI scale revealed a significant gender difference, with men showing a more positive orientation toward AI in healthcare. This suggests that gender differences may become more visible when attitudes are evaluated in a concrete application context rather than at a general level.

Table 21: Variability of ChatGPT attitudes across groups (N=172, mean, SD)

Group	Mean	SD
Male	13.91	4.15
Female	11.86	3.55
Younger (18–28)	12.72	4.07
Older (29–44)	13.40	2.59

Tests: t-test for two-group comparisons; one-way ANOVA for income groups.
Interpretation: ns = not significant ($p > 0.05$)
$p < 0.05$ significant ($p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)*
Source: Author's own calculation based on the primary survey dataset (N = 172).

An additional layer of analysis reveals differences not only in mean values but also in variability across groups (Table 21). Younger respondents display higher variability in their responses, suggesting less stable or more uncertain attitudes toward ChatGPT.

In contrast, older respondents show more consistent evaluations, which may indicate more consolidated opinions.

Education again plays an important role. Respondents with higher educational attainment reported significantly lower negative attitudes toward robots. This pattern suggests that education may reduce emotional resistance to automation, possibly by increasing familiarity with technology or by shaping more nuanced expectations about its use.

At the same time, education did not significantly influence the 8-item healthcare AI scale. This indicates that while education may reduce general discomfort with robots, it does not necessarily translate into more positive evaluations of AI in specific healthcare contexts.

An important distinction emerges between general attitudes toward automation and evaluations of specific AI applications. Negative attitudes toward robots reflect broader emotional responses, such as fear of loss of control or discomfort with autonomous systems.

However, these general attitudes do not strongly translate into specific evaluations of ChatGPT. This suggests that respondents differentiate between abstract perceptions of automation and concrete tools with which they may interact directly. In other words, emotional resistance toward robots does not automatically imply rejection of all AI applications. Instead, acceptance appears to depend on the perceived function and context of the technology.

This distinction highlights the importance of separating general attitudes toward AI from evaluations of specific tools. While abstract perceptions may be shaped by broader narratives, concrete applications such as ChatGPT trigger more immediate concerns related to trust and practical use.

Although the 8-item scale is presented in aggregated form, item-level inspection indicates that respondents are more positive toward efficiency and technological support, while more cautious regarding autonomy and decision-making roles of AI.
This suggests that acceptance of AI in healthcare is selective and depends on the perceived function of the technology.

6.4 Perceptions of ChatGPT in Healthcare

Among the examined constructs, ChatGPT stands out as the most contested. The overall mean score (12.77) suggests cautious attitudes, with respondents neither clearly rejecting nor strongly endorsing its use in healthcare.

A notable pattern emerges when looking at gender differences. Male respondents scored significantly higher on the ChatGPT scale than female respondents (13.91 vs. 11.86, $p < 0.001$). This is the strongest demographic effect observed in the dataset and indicates that acceptance of conversational AI may be more sensitive to gender-related differences in risk perception and trust.

In contrast, neither education nor age showed a significant relationship with ChatGPT attitudes. This is particularly interesting given the strong role of education in digital health literacy. It suggests that trust in ChatGPT is not simply a function of competence but is shaped by other factors, such as perceived reliability and the nature of the task.

To gain a more detailed understanding, the five ChatGPT-related items were analyzed separately (Table 22).

Table 22: Item-level analysis of ChatGPT attitudes (N = 172)

Statement	Mean	SD
1. I consider ChatGPT to be a reliable source for questions about my medical and health conditions.	2.55	0.95
2. In my opinion, the usage of ChatGPT has a positive impact on the health literacy of society.	2.90	0.85
3. I ask health questions to ChatGPT more often than to a doctor.	1.80	0.90
4. I would rather go to ChatGPT with uncomfortable, overly personal questions than see a doctor in person.	2.40	0.92
5. I believe that ChatGPT will soon be part of everyday healthcare.	3.12	0.88

Scale: 1–5 (higher = stronger agreement)
Source: Author's own calculation

As shown in Table 23, ChatGPT-related attitudes differ from the other constructs in terms of their underlying determinants. The results indicate that gender is the only sociodemographic variable showing a statistically significant relationship with ChatGPT attitudes ($p = 0.0008$). This suggests that male and female respondents differ meaningfully in their overall evaluation of ChatGPT in healthcare contexts. A more detailed examination of group means reveals that male respondents reported higher levels of trust and openness toward ChatGPT (Mean = 13.91), compared to female respondents (Mean = 11.86). This difference suggests that gender-related differences in risk perception or trust may influence the acceptance of conversational AI in healthcare.

Table 23: Statistical significance of group differences in ChatGPT attitudes (N=172)

Grouping variable	p-value	Interpretation
Gender	0.0008	***
Age	0.5239	ns
Residence	0.0188	*
Relative income	0.0864	ns
Highest completed education	0.8750	ns
Ongoing studies	0.8153	ns

Tests: t-test for two-group comparisons; one-way ANOVA for income groups.
Interpretation: ns = not significant ($p > 0.05$)
$p < 0.05$ significant ($p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)*
Source: Author's own calculation based on the primary survey dataset (N = 172).

In contrast, education, age, and income do not significantly influence ChatGPT perceptions. This is particularly noteworthy given the strong role of education in shaping digital health literacy and general attitudes toward automation. These findings suggest that attitudes toward ChatGPT are not primarily driven by competence-related factors, but rather by trust, perceived risk, and contextual evaluation. This reinforces the idea that conversational AI is assessed differently from more familiar digital tools. The results reveal a more nuanced picture than the composite score alone. Trust in ChatGPT as a source of medical information is relatively low, indicating that respondents are hesitant to rely on it in situations involving personal health.

When the results are considered together, a clear pattern emerges across constructs. Education consistently influences digital health literacy and negative attitudes toward robots, but has no effect on ChatGPT-related perceptions. Gender, on the other hand, shows the opposite pattern: it has little impact on general attitudes, but becomes highly significant in the case of ChatGPT.

At the same time, variables such as age, income, and place of residence show only limited or inconsistent effects. This suggests that attitudes toward AI in healthcare are not strongly structured by traditional sociodemographic factors alone.

Instead, the results point to a distinction between competence-driven and trust-driven evaluations. While education shapes perceived ability and general attitudes, acceptance of ChatGPT appears to depend more strongly on perceived reliability, uncertainty, and risk. At the same time, the perceived societal usefulness of ChatGPT receives more positive evaluations. This suggests that respondents differentiate between personal reliance and broader informational benefits.

The strongest rejection appears in relation to the idea of replacing doctors. This item consistently receives the lowest level of agreement, indicating a clear boundary between AI as a supportive tool and AI as a substitute for professional care. Attitudes toward using ChatGPT for sensitive or embarrassing topics are more mixed. While a portion of respondents see value in the privacy offered by AI, others remain hesitant. This reflects a tension between convenience and trust.

Finally, expectations regarding future integration are relatively high. Even respondents who are cautious about current use tend to believe that ChatGPT will become part of everyday healthcare in the near future.

Taken together, these item-level patterns show that attitudes toward ChatGPT are structured rather than random. Respondents are willing to accept AI in certain roles but draw clear boundaries when it comes to trust and substitution. A key feature of ChatGPT-related attitudes is the coexistence of cautious evaluation and relatively high expectations for future integration. This apparent contradiction suggests that respondents distinguish between current limitations and anticipated technological development.

Another important dimension is the difference between personal and societal evaluation. While respondents are hesitant to rely on ChatGPT for their own health decisions, they are more willing to acknowledge its potential contribution at the societal level. This may reflect a form of indirect acceptance, where individuals recognize benefits in principle but remain cautious in practice.

The rejection of doctor replacement is particularly noteworthy. This boundary appears consistently across responses and indicates that respondents maintain a clear distinction between professional medical expertise and AI-based support tools. Rather than viewing

ChatGPT as a substitute, respondents position it within a supplementary role. This distinction aligns with broader patterns observed in digital health adoption, where users are willing to engage with technology as a support mechanism, but not as a replacement for human expertise.

This divergence suggests that respondents distinguish between expected future usefulness and current trust. While they anticipate the integration of ChatGPT into healthcare systems, they remain hesitant to rely on it in personal decision-making contexts. This indicates a temporal gap between perceived potential and present acceptance. A further internal contradiction can be observed between individual items. While respondents strongly reject the idea of replacing doctors, they simultaneously express openness to using ChatGPT for sensitive or personal questions. This indicates that acceptance is conditional rather than general. Respondents are willing to use AI in specific contexts, particularly where privacy is important, but maintain clear boundaries regarding its role in healthcare.

6.5 Sociodemographic Patterns in AI and ChatGPT Attitudes

While individual group comparisons were discussed in the previous sections, it is useful to consider the broader pattern that emerges across sociodemographic variables.

Table 24: Summary of main patterns across constructs (N=172)

Construct	Direction	Key driver	Interpretation
eHEALS	High	Education	Strong perceived competence
NARS	Neutral	Education	Moderate emotional resistance
AI attitudes	Slightly positive	Gender	General openness
ChatGPT	Low / mixed	Gender	Trust-related hesitation

Source: Author's own calculation

Across all variables, education stands out as the most consistent factor shaping attitudes (Table 24). Higher educational attainment is associated with stronger digital health literacy and lower negative attitudes toward robots. At the same time, this effect does not extend to ChatGPT attitudes, where no significant relationship with education was observed. This suggests that familiarity with digital information does not automatically translate into trust in conversational AI.

Gender, in contrast, shows a selective but notable effect. While differences are minimal for eHEALS and NARS, they become substantial for ChatGPT-related attitudes. This indicates that gender differences are more likely to emerge in contexts where trust, uncertainty, and perceived risk play a central role.

Age effects are less pronounced within the student sample, which is largely homogeneous and concentrated in younger cohorts. Although older respondents within the sample tend to report slightly higher digital literacy and more positive attitudes toward AI, these differences remain descriptive rather than statistically significant.

Place of residence and income show only minor effects. While urban respondents and financially secure individuals tend to display slightly more positive attitudes, these patterns are not strong enough to be considered robust within this dataset.

Therefore, the results suggest that education shapes competence and general attitudes, while trust in ChatGPT follows a different logic, one that is less dependent on structural factors and more closely tied to perceived reliability and risk.

These findings suggest a distinction between structural and psychological determinants of technology acceptance. Structural factors, such as education, influence competence and general attitudes, while psychological factors, including trust and perceived risk, play a more central role in shaping attitudes toward specific tools such as ChatGPT. This distinction helps explain why education does not significantly affect ChatGPT attitudes, despite its strong association with digital health literacy. Trust in conversational AI appears to be driven less by knowledge and more by perceived reliability and uncertainty.

6.6 Interrelationships Between Digital Competence, AI Attitudes, and ChatGPT Perceptions

To explore how the examined constructs relate to each other, a series of linear regression analyses were conducted.

Table 25. Linear regression analyses (scale totals, N=172)

Variables	R^2
eHEALS vs NARS	0.00003
8-item (AI attitude) scale vs eHEALS	0.0528
8-item (AI attitude) scale vs NARS	0.0119
5-item (ChatGPT) scale vs eHEALS	0.0676
5-item (ChatGPT) scale vs NARS	0.0220
5-item (ChatGPT) scale vs 8-item (AI attitude) scale	0.3008

Source: Author's own calculation

The results show generally weak relationships between the variables (Table 25). Digital health literacy (eHEALS) explains virtually none of the variance in negative attitudes toward robots ($R^2 \approx 0.000$). This suggests that being confident in handling online health information does not necessarily reduce discomfort with automation.

Similarly, the relationship between eHEALS and the two attitude scales remains limited. Digital health literacy accounts for only a small proportion of the variance in both general AI attitudes and ChatGPT perceptions. In practical terms, this means that competence and acceptance are only loosely connected.

Associations involving NARS are even weaker. Negative emotional attitudes toward robots do not strongly predict either general AI attitudes in healthcare or specific perceptions of ChatGPT.

The only substantial relationship emerges between the two self-developed scales: the 8-item AI attitude scale and the 5-item ChatGPT scale. With an R^2 of approximately 0.30, this indicates a moderate connection. Respondents who are generally more open to AI in healthcare also tend to view ChatGPT more positively.

This result is important because it suggests that ChatGPT attitudes are not isolated, but are embedded within a broader evaluative framework regarding AI in healthcare. At the same time, the relatively low explanatory power of the other models highlights that trust in conversational AI cannot be reduced to general digital competence or emotional attitudes toward automation.

The generally low explanatory power of the regression models suggests that the examined variables capture only part of the underlying mechanisms. Attitudes toward ChatGPT are likely influenced by additional factors not included in the model, such as prior experience with AI, trust in technology providers, and perceived risks associated with incorrect information. This limitation does not reduce the relevance of the findings; rather, it highlights the complexity of AI acceptance in healthcare contexts.

The weak relationships observed in the models suggest that attitudes toward ChatGPT are influenced by additional factors not captured in the present analysis. These may include prior experience, perceived reliability, and trust in information sources, highlighting the multidimensional nature of AI acceptance in healthcare.

These findings suggest that the acceptance of ChatGPT is a multidimensional phenomenon that cannot be explained by a single predictor. Instead, it reflects the combined influence of competence, trust, and perceived risk.

The weak explanatory power of most regression models further supports this interpretation. Traditional predictors such as competence and general attitudes explain only a limited proportion of variance in ChatGPT-related perceptions. This suggests that acceptance of conversational AI is influenced by additional factors not captured in the present analysis. Rather than indicating a lack of structure, these weak relationships highlight the complexity of the phenomenon. ChatGPT occupies a distinct position within the broader AI landscape, where evaluations are shaped by a combination of competence, trust, and perceived risk. This align with broader findings suggesting that structurel and cultural factors alone are insufficient to explain complex behavioral outcomes, as multiple interacting determinants shape attitudes and adaptation patterns (Végh et al., 2025).

6.7 Results of the Representative 40+ Survey

The second dataset provides insight into how older population groups perceive ChatGPT in healthcare contexts. The same five items were used as in the student survey, although responses were measured on a 4-point scale (1=totally agree, 4=totally disagree) without a neutral midpoint (Table 26)

Table 26: Descriptive Statistics on Attitude towards health-related usage of ChatGPT survey (N=200)

	Statement 1 I consider ChatGPT to be a reliable source for questions about my medical and health conditions.	Statement 2 In my opinion, the usage of ChatGPT has a positive impact on the health literacy of society.	Statement 3 I ask health questions to ChatGPT more often than to a doctor.	Statement 4 I would rather go to ChatGPT with uncomfortable, overly personal questions than see a doctor in person.	Statement 5 I believe that ChatGPT will soon be part of everyday healthcare
Total (number)	200	200	200	200	200
Strongly agree (%)	5	9	5	7	10
Rather Agree (%)	42	46	20	33	51
Rather disagree (%)	30	22	29	32	20
Strongly disagree (%)	23	23	47	29	20
Mean	2.71	2.59	3.17	2.84	2.49
StD	0.88	0.94	0.92	0.92	0.92
Mode	2	2	4	2	2
Median	3	3	2	2	3

Source: Author's own data collection

The results indicate a generally cautious stance. Only a small proportion of respondents strongly agree that ChatGPT is a reliable source of medical information, while a clear majority express some level of disagreement. The mean values suggest moderate skepticism, especially when questions involve personal health. At the same time, respondents are more positive when evaluating the broader societal impact of ChatGPT. Many agree that it may contribute to improving health literacy at a population level. This distinction between personal trust and societal usefulness appears consistently across the data.

The rejection of doctor replacement is particularly strong. A large majority of respondents disagree with the idea that they would turn to ChatGPT more often than to a physician. This indicates a clear boundary in how AI is perceived: as a supplementary tool rather than a substitute.

Attitudes toward sensitive topics are more nuanced. A substantial minority of respondents indicate that they would prefer ChatGPT for private or embarrassing questions, suggesting that conversational AI may fill a niche where anonymity and accessibility are valued.

Finally, expectations regarding future integration are relatively high. Despite current reservations, many respondents believe that ChatGPT will become part of everyday healthcare practice.

Table 27: Gender differences based on the survey (N=200)

	Total Mean	Statement1	Statement2	Statement3	Statement4	Statement5
Male	2.74	2.66	2.58	3.14	2.85	2.48
Female	2.78	2.76	2.60	3.19	2.82	2.51
Difference (male compared to female)	0.99	0.96	0.99	0.98	1.01	0.99
Gender difference%	1	4	1	2	1	1

Source: Author's own data collection

Gender differences in the 40+ sample are present but relatively small and statistically non-significant (Table 27). Male respondents tend to report slightly higher levels of trust and openness across all five items, but the magnitude of these differences remains limited, typically ranging between 1–4%. This indicates that while gender differences exist, they do not represent a strong differentiating factor in this age group. This contrasts with the student sample, where gender differences were more pronounced, particularly for the composite ChatGPT scale.

The consistency of the direction across both datasets suggests that gender plays a role, but its strength may vary depending on age and context.

More substantial variation emerges when examining generational differences within the 40+ sample. The results presented in Table 28 reveal clear generational differences in attitudes toward ChatGPT in healthcare.

Respondents in their early 40s display the highest levels of acceptance across most items. In contrast, older groups—particularly Baby Boomers—express more skepticism, especially regarding trust and the use of ChatGPT in place of traditional medical consultation. Generation X respondents expressed more cautious attitudes, while Baby Boomers exhibited the strongest skepticism, particularly with respect to trust and behavioral substitution.

Table 28: Descriptive statistics of generations based on generation classification (Zhang and Dafoe, 2019) (N=200)

		Millennials/ Generation Y (N=20) (1981-1996)	Generation X (N=104) (1965-1980)	Baby boomers (N=75) (1946-1964)
Statement 1 I consider ChatGPT to be a reliable source for questions about my medical and health conditions.	Mean	2.55	2.68	2.77
	SD	0.89	0.90	0.85
	% of Agree *	60	47	44
Statement 2 In my opinion, the usage of ChatGPT has a positive impact on the health literacy of society.	Mean	2.55	2.51	2.71
	SD	0.95	0.94	0.96
	% of Agree*	55	59	51
Statement 3 I ask health questions to ChatGPT more often than to a doctor.	Mean	2.57	3.12	3.33
	SD	1.02	0.94	0.83
	% of Agree*	45	29	15
Statement 4 I would rather go to ChatGPT with uncomfortable, overly personal questions than see a doctor in person.	Mean	2.45	2.75	3.04
	SD	0.95	0.90	0.91
	% of Agree*	55	44	28
Statement 5 I believe that ChatGPT will soon be part of everyday healthcare	Mean	2.50	2.42	2.57
	SD	0.89	0.93	0.92
	% of Agree*	65	62	59
Total	Mean	2.56	2.70	2.89

**% of Agree is a combined result of replies to totally agree and agree*
Source: Author's own data collection

The most pronounced differences appear in relation to behavioral use and substitution. For Statement 3 ("I ask health questions to ChatGPT more often than to a doctor"), agreement declines sharply across generations, from 45% among Millennials to only 15% among Baby Boomers. A similar pattern is observed for sensitive use (Statement 4), where younger respondents are considerably more open to using ChatGPT for personal or uncomfortable questions.

In contrast, differences are less marked for societal-level evaluation and future expectations. For example, agreement with the statement that ChatGPT will become part of everyday healthcare remains relatively high across all generations (65%, 62%, and 59%, respectively). This suggests that while personal trust and usage decrease with age, expectations regarding future integration are broadly shared.

Interestingly, perceived reliability (Statement 1) does not differ as strongly as behavioral indicators. Although younger respondents report higher agreement, the differences are moderate, indicating that skepticism is present across all age groups.

Overall, the findings point to a clear generational gradient: acceptance of ChatGPT decreases with age, particularly in contexts involving direct use and substitution of traditional healthcare interactions. At the same time, the relatively stable expectations regarding future integration suggest that even more skeptical groups recognize the growing role of AI in healthcare systems.

The results presented in Table 29 confirm that generational differences in attitudes toward ChatGPT are selective rather than uniform across all dimensions. Statistically significant differences are observed only in relation to behavioral use and sensitive contexts, while other aspects remain largely consistent across age groups.

Table 29: Generational differences in attitudes toward ChatGPT in healthcare (Secondary dataset, N = 200)

ChatGPT-related statement (5-item scale)	Millennials (40–43)	Generation X (44–59)	Baby Boomers (60–78)	Statistical test	p-value	Significance
Statement 1 **I consider ChatGPT to be a reliable source for questions about my medical and health conditions.**	Highest mean (2.55) (SD=0.89)	Moderate mean (2.68) (SD=0.90)	Lowest mean (2.77) (SD=0.85)	ANOVA	> 0.05	ns
Statement 2 **In my opinion, the usage of ChatGPT has a positive impact on the health literacy of society.**	Similar means across groups (2.55) (SD=0.95)	Similar means across groups (2.51) (SD=0.94)	Similar means across groups (2.71) (SD=0.96)	ANOVA	> 0.05	ns
Statement 3 **I ask health questions to ChatGPT more often than to a doctor.**	Highest mean (2.57) (SD=1.02)	Lower mean (3.12) (SD=0.94)	Lowers mean (3.33) (SD=0.83)	ANOVA	0.05	*
Statement 4 **I would rather go to ChatGPT with uncomfortable, overly personal questions than see a doctor in person.**	Highest mean (2.45) (SD=0.95)	Moderate mean (2.75) (SD=0.90)	Lowest mean (3.04) (SD=0.91)	ANOVA	0.02	*
Statement 5 **I believe that ChatGPT will soon be part of everyday healthcare**	Similar means across groups (2.50) (SD=0.89)	Similar means across groups (2.42) (SD=0.93)	Similar means across groups (2.57) (SD=0.92)	ANOVA	> 0.05	ns

(Note: group comparisons based on mean differences across generations, lower mean values idicate higher acceptance/trust. Generational grouping based on age at time of data collection.)
*ns = not significant (p > 0.05), * = significant at p < 0.05*
Lower mean values indicates higher acceptance/trust (1=totally agree, 4=totally diragree)
Source: Author's own data collection

The interpretation of mean values is based ont he scale direction, where lower values indicate higher levels of agreement and higher acceptance of ChatGPT. Accordingly, Millennials consistently show lower mean values across most items, indicating the highest level of acceptance, while Baby Boomers show the highest mean values, reflelecting lower acceptance.

Specifically, significant generational effects emerge for Statement 3 (“I ask health questions to ChatGPT more often than to a doctor”, p = 0.05) and Statement 4 (“I would rather go to ChatGPT with uncomfortable, overly personal questions than see a doctor in person", p = 0.02). In both cases, younger respondents show higher levels of acceptance, while older groups—particularly Baby Boomers—demonstrate more cautious attitudes. This indicates that generational differences are most pronounced in situations involving direct interaction and potential substitution of traditional healthcare pathways.

In contrast, no significant differences are found for perceived reliability (Statement 1), societal impact (Statement 2), or expectations regarding future integration (Statement 5). The relative stability of these dimensions suggests that broader evaluations of ChatGPT are less sensitive to generational differences than concrete behavioral intentions.

These indings indicate that generational effects are context-dependent. Age influences how individuals are willing to use ChatGPT in practice, particularly in personal or sensitive situations, but has a more limited impact on general perceptions or expectations. This reinforces the interpretation that acceptance of conversational AI is structured around specific use cases rather than uniformly distributed attitudes. Therefore, age-related differences are not uniform across all dimensions. While trust and behavioral intention vary with age, broader expectations about technological development appear more stable.

6.7.1 Differences in ChatGPT Attitudes Between Studens and 40+ Samples

Before comparing the two datasets, it is important to acknowledge that they differ in sampling strategy and measurement scale. The student survey used a 5-point Likert scale, while the representative survey employed a 4-point forced-choice format. For this reason, the comparison is not intended as a direct statistical comparison but as an interpretative alignment of patterns. Table 30 presents a structured comparison of ChatGPT related attitudes across the two datasets.

Table 30: Comparison of ChatGPT-Related Attitudes Across the Two Datasets (standerdised interpretation and original metrics, N=172/200)

Dimension	Primary sample – University students (N = 172, 5-point Likert)	Secondary sample – 40+ population (N = 200, 4-point forced choice)	Interpretation
Trust in ChatGPT as a medical information source	Mean = 12.77, SD = 3.94 (5–25 scale)	5% strongly agree, 42% rather agree, 53% disagree	Lower and more clearly bounded trust in older sample
Replacement of doctors by ChatGPT	Lowest mean within 5-item scale (Statement 3); clear disagreement	78% disagree (rather + strongly disagree)	Strong rejection in both samples
Use of ChatGPT for sensitive / personal health questions	Moderate endorsement; item mean close to scale midpoint	39% agree, 61% disagree	Conditional acceptance across both groups
Gender differences (ChatGPT scale)	Men: 13.91, Women: 11.86, p = 0.0008*	Men slightly higher across all items ($\Delta \approx$ 1–4%), ns	High expectation in both samples
Age / generational effects	Descriptive differences only; not significant (p = 0.739)	Significant generational effects: substitution (p = 0.05), sensitive use (p = 0.02)	Stronger in student sample
Expectation of future integration into healthcare	Moderate–positive endorsement (item-level means above midpoint)	61% agree ChatGPT will become part of healthcare	Emerges only in 40+ sample
Overall acceptance pattern	Cautious openness, uncertainty	Lower trust, clearer and stricter role boundaries	Structured but context-dependent acceptance

Source: Based on Author's own data analysis

Several consistent patterns emerge across the two datasets. First, substitution of doctors by ChatGPT is clearly rejected in both datasets. In the student sample, the mean score for the item "I ask health questions to ChatGPT more often than to a doctor" was 12.77 (SD = 3.94) on the 5-item composite, with this statement receiving the lowest endorsement among all ChatGPT-related items. In the representative 40+ sample, 78% of respondents disagreed with this statement, indicating a strong and consistent rejection of behavioral substitution across age groups.

Second, trust in ChatGPT is lower and more clearly delimited in the secondary sample. Among students, the overall ChatGPT scale mean (12.77) reflects cautious openness with high variability, suggesting uncertainty rather than firm rejection. In contrast, only 5% of respondents aged 40+ strongly agreed that ChatGPT is a reliable source for medical questions, while 53% expressed disagreement, indicating lower trust but more clearly articulated boundaries regarding acceptable use.

Third, age and generational gradients are substantially stronger in the secondary dataset. In the student sample, age-related differences (18–28 vs. 29–44) were descriptive and not statistically significant (e.g., ChatGPT scale: $p = 0.739$). In contrast, the representative dataset revealed statistically significant generational effects, with ANOVA confirming differences for: asking ChatGPT health questions more often than a doctor ($p = 0.05$), and preferring ChatGPT for sensitive or personal health questions ($p = 0.02$). Respondents in their early 40s consistently showed the highest acceptance levels, while Baby Boomers exhibited the strongest skepticism.

Fourth, expectations of future integration converge across datasets despite differing trust levels. In the student sample, future integration was among the more positively rated ChatGPT-related items. Similarly, in the representative sample, 61% agreed that ChatGPT will soon become part of everyday healthcare. This convergence indicates shared expectations of systemic adoption, even where personal trust and behavioral intention remain limited.

These findings suggest that acceptance of ChatGPT is structured by clear role expectations. Respondents are willing to accept AI in supportive roles, but remain reluctant to extend this acceptance to domains requiring high levels of trust and responsibility.

6.8 Digital Health Usa and Trust in Hungary: Contextual interpretation

Secondary data show that 73% of the Hungarian population uses the internet for health-related information, with usage peaking at 90% among younger users. Usage is particularly high among younger cohorts: 90% among individuals aged 16–29, compared to 53% among those aged 55 and above. At the same time, only 63% of the Hungarian population possesses at least basic digital skills, highlighting a clear gap between widespread online engagement and underlying digital competence. (Table 31).

Table 31: Digital Skills and Online Health Information Use (source: Eurostat)

Indicator	Hungary (%)	EU average (%)
Population with at least basic digital skills	63	54
Internet use for health-related information (total)	73	75
Internet use for health information (ages 16–29)	90	88
Internet use for health information (ages 55+)	53	57

Source: Eurostat (2023), Digital skills indicator (isoc_sk_dskl_i); Internet use for health information (isoc_ci_ac_i)

This discrepancy mirrors patterns observed in the primary student survey, where high eHEALS scores (Mean = 28.69 / 40) coexisted with cautious attitudes toward AI-based health tools. The secondary data thus reinforce the notion that high exposure to digital health information does not automatically translate into confident or critical use.

Secondary data show that the use of the internet for health-related information is widespread in Hungary, particularly among younger age groups. At the same time, the proportion of individuals with at least basic digital skills is considerably lower.
This gap between usage and competence mirrors the pattern observed in the student sample. High levels of engagement with digital health information do not necessarily translate into confident or critical use.

Trust-related indicators reveal a pronounced trust–risk imbalance. Only 28% of Hungarian respondents report high trust in digital health services, while 62% express concern about AI-related medical errors (Table 32). Willingness to rely on digital tools for health decisions remains similarly low (26%).

Table 32: Trust and Risk Indicators Related to Digital Health and AI (source: Eurobarometer)

Indicator	Hungary (%)	EU average (%)
High trust in digital health services	28	41
Willingness to rely on digital tools for health decisions	26	39
Concern about AI-related medical errors	62	58

Source: Eurobarometer (2022), Special Eurobarometer 516 – European citizens' knowledge and attitudes towards science and technology; OECD (2022), Health at a Glance: Europe – Digital Health Indicators.

These population-level figures closely correspond to the primary survey results, where the ChatGPT in healthcare scale reached only 12.77 out of 25 (≈51%), indicating moderate-to-low trust even in a young, digitally skilled sample. These findings align closely with the survey results, where ChatGPT is viewed with caution even among digitally experienced respondents. This convergence suggests that skepticism toward AI in healthcare is not limited to specific groups but reflects a broader pattern.

Secondary statistics show a clear and stable pattern: acceptance of AI in a supportive role exceeds 60%, while acceptance of AI replacing medical professionals remains limited to roughly one quarter of respondents (Table 33). This distinction between support and substitution provides an important benchmark for interpreting the primary survey findings, where explicit rejection of doctor replacement exceeded 75% in both primary samples.

Table 33: Acceptance of AI Roles in Healthcare (Source: Euroberometer, OECD)

Indicator	Hungary (%)
Acceptance of AI as supportive tool	58–64
Acceptance of AI replacing doctors	22–26

Source: calculated by author based on based on: European Commission (2022). Special Eurobarometer 516: European citizens' knowledge and attitudes towards science and technology and OECD (2022). Health at a Glance: Europe 2022 – Digital Health Indicators.

The secondary data confirm and contextualize the primary survey findings (Table 34). Across all data sources, three quantitatively consistent patterns emerge:

- High digital engagement does not imply high trust: despite widespread internet use for health information (73–90%), trust in digital health tools remains below 30%.
- Substitution is consistently rejected: acceptance of AI replacing doctors remains low across datasets, clustering between 22–26%.
- Future integration is widely anticipated: expectations of AI becoming part of healthcare exceed 60% in both primary and secondary data.

Table 34: Comparison of digital competence and AI attitudes across aata sources (%, N vaies by dataset)

Dimension	Primary survey (students)	Secondary data
Digital competence	72%	63% basic skills
Trust in digital health / AI	51%	28% high trust
Willingness to replace doctors	< 25%	22–26%
Use for sensitive topics	~ 35–40%	30–40%
Expect AI integration into healthcare	~ 60%	59–67%

Source: Primary student survey (N = 172), author's own data collection (2024–2025); Eurostat (2023), Digital skills indicator (isoc_sk_dskl_i) and Internet use for health information (isoc_ci_ac_i); European Commission (2022), Special Eurobarometer 516;OECD (2022), Health at a Glance: Europe – Digital Health.

The comparison is structured according to analytical relevance. Generational patterns are primarily interpreted using the 40+ sample, while trust, behavioral intention, and substitution-related attitudes are benchmarked against the student sample, which serves as the baseline for early-stage adoption patterns.

Secondary datasets consistently report strong age-related gradients in digital health engagement and AI acceptance. According to Eurostat (2023), health-related internet use declines from 90% among younger adults to 53% among individuals aged 55+, while trust in digital health tools also decreases with age (Eurobarometer, 2022). The generational gradient observed in secondary statistics is numerically reproduced in the 40+ dataset. Respondents in their early 40s demonstrate acceptance levels that are substantially closer to the student sample than to older cohorts, while Baby Boomers consistently express the lowest trust and willingness across all indicators. ANOVA results confirmed statistically significant generational effects for: behavioral substitution ($p = 0.05$), and comfort with sensitive topics ($p = 0.02$). Thus, the 40+ sample functions as a bridge dataset, empirically linking population-level secondary indicators with micro-level survey findings.

Secondary data indicate that only 26–28% of respondents in Hungary report high trust in digital health or AI-based health tools (Eurobarometer, 2022), while concern about AI-related medical errors reaches 62% (OECD, 2022). These figures closely align with the student survey results: Mean ChatGPT scale score: 12.77 / 25 (≈51%), Explicit substitution support: below 25%, and Expectation of future integration: ~60% (Table 35). Across all three data sources, trust-related indicators converge within a narrow numerical range. While the student sample reports slightly higher openness, this difference diminishes when evaluated against substitution-related items, where rejection remains strong in all datasets. Table 35 compares three distinct data sources: the primary student survey, the representative 40+ survey, and secodary statistical indicators at the national and European level.

Table 35: Comparison of trust and behavioral intention across primary, secondary and representatice survey data (%, N=172/200/EU datasets)

Indicator	Student sample (N = 172)	40+ sample (N = 200)	Secondary data
Trust in AI/digital health	51% (scale-based)	~33%	26–28%
Willingness to replace doctors	<25%	~20%	22–26%
Use for sensitive topics	~38%	~39%	30–40%
Expect AI integration	~60%	~61%	59–67%

Source: Calculated from: Primary student survey (N = 172), author's own data collection (2024–2025); Representative 40+ survey (N = 200), author's own data collection (2024); Eurostat (2023), Digital skills and internet use for health information; European Commission (2022), Special Eurobarometer 516; OECD (2022), Health at a Glance: Europe – Digital Health Indicators.

When the three data sources are considered together, a consistent picture emerges. The triangulated comparison reveals three stable, data-supported regularities:

1. Generational decline is robust and consistent: Acceptance decreases systematically with age in secondary data and is replicated quantitatively in the 40+ sample.
2. Early adoption does not imply substitution: Despite higher digital literacy in the student sample (eHEALS Mean = 28.69), substitution support remains below 25%, consistent with secondary benchmarks.
3. Future integration expectations converge: All datasets report expectations above 60%, indicating perceived inevitability despite current skepticism.

Table 36 demonstrates strong convergence across all three data sources. While absolute trust levels differ by age and sample composition, rejection of substitution, conditional use for sensitive topics, and expectations of future integration show remarkably stable numerical patterns, supporting the robustness of the findings across generations and data types.

Table 36: Triangulation of Findings Across Data Sources: Trust, Behavioral Intention, and Generational Effects (N=172/200/EU datasets)

Dimension	Primary student sample (N = 172)	Representative 40+ sample (N = 200)	Secondary data (HU / EU)
Trust in AI / ChatGPT for health information	Mean = 12.77 / 25 (≈51%)	Agree ≈ 33% overall	High trust: 26–28%
Rejection of doctor substitution	>75% reject replacement	≈78% reject replacement	74–78% reject replacement
Use for sensitive / personal topics	≈38% agree	≈39% agree	30–40%
Expectation of future healthcare integration	≈60% agree	≈61% agree	59–67%
Gender effect on ChatGPT attitudes	Significant ($p < .001$), men higher	Small, consistent differences	Weak but stable
Education effect on ChatGPT trust	Not significant ($p = .875$)	Not significant	Not decisive
Generational gradient (trust & use)	Descriptive only (ns)	Significant ($p = .05$; $p = .02$)	Strong age gradient
Role perception of AI	Supplementary, not substitutive	Clearly bounded, supplementary	Supportive / assistive

Sources: Sources: Primary student survey (N = 172), author's own data collection (2024–2025); Representative 40+ population survey (N = 200), author's own data collection (2024); Eurostat (2023), isoc_sk_dskl_i; isoc_ci_ac_i; European Commission (2022), Special Eurobarometer 516; OECD (2022), Health at a Glance: Europe 2022.

In conclusion, acceptance of AI in healthcare declines with age, but this decline is gradual rather than absolute. Second, even among younger and more digitally skilled respondents, support for replacing doctors remains limited. Third, expectations regarding the future role of AI are relatively high across all groups. These findings suggest that attitudes toward AI in healthcare are shaped by a combination of competence, trust, and role perception. While digital literacy enables engagement, it does not eliminate concerns about reliability and accountability. As a result, AI is primarily viewed as a complementary tool rather than a substitute for professional care.

7. CONCLUSIONS AND RECOMMENTATIONS

The present dissertation set out to examine public acceptance of ChatGPT in healthcare contexts in Hungary, with particular attention to demographic factors, trust formation, and the applicability of established technology acceptance models. Drawing on a primary student-based survey, a representative 40+ population sample, and secondary statistical data, the research provides a multi-layered and empirically grounded account of AI acceptance in a sensitive, high-stakes domain. This chapter summarizes the key conclusions of the dissertation and formulates recommendations for healthcare practice, policy, and future research.

7.1 Hypotheses, Measurement, Analysis, and Outcomes

Table 37 provides a transparent overview of how each objective and hypothesis was operationalised, which questionnaire items captured the construct, how the analysis was performed, what result was obtained, and how this contributes to the dissertation’s new scientific contribution. Objective 1 serves as a theoretical foundation for the development of the dissertation’s hypotheses (H1-H5), as the literature review informs the selection of key variables such as demographic characteristics, trust, perceived usefulness, and behavioral intention. Namely, H1, H2 and H5 grounded in the literature rewies, which consistently highlights the influence of variables such as age and educational attainment based on tehcnology. H3 also rooted in established theoritical frameworks, particularly the UTAUT model and emerging AI trust models, while H4 is diretly dericed from UTAUT framework, which emphasized the moderating role of demographiy characteristics in the relationship between perceived usefulness and behavioral intention.

Table 37: Overview of objectives, hypotheses, operationalisation, analysis, results, and contributions

Objective	Hypothesis	Research topic	Questionnaire item(s) / measure(s)	Analysis method	Result	New scientific contribution
Obj. 2–3 (Obj. 1)	H1: Younger individuals demonstrate higher acceptance and trust toward ChatGPT for health-related use	Age / generation and acceptance	Student sample: age groups (18–28 vs 29–44) + ChatGPT 5-item scale; 40+ sample: generation groups + 5 UTAUT-aligned items	t-test/ANOVA + subgroup comparisons	**Partially accepted**: stronger generational gradient in 40+ sample; student sample age effects mostly descriptive	Shows that "digital nativity" does not automatically imply higher acceptance; life-stage relevance matters
Obj. 3 (Obj. 1)	H2: Demographic characteristics significantly influence acceptance, with different strengths across variables	Demographic moderators	Gender, age, residence, income, education + eHEALS, NARS, 8-item, 5-item	Group comparisons (t-test/ANOVA)	**Accepted:** effects are selective and construct-specific (e.g., gender significant for ChatGPT attitudes; education significant for eHEALS and NARS)	Demonstrates that "demographics" is not a single effect but differs by outcome construct
Obj. 4 (Obj. 1)	H3: Higher trust is positively associated with perceived usefulness and intention to use	Trust–use mechanism	Student sample: relationships among scales (regression; 8-item vs 5-item strongest) + interpretation within UTAUT	Linear regression + interpretation	**Accepted** (with nuance): trust-related attitudes move together with context-specific AI attitudes; strongest link between the two custom scales	Empirically supports trust as a key mechanism linking perceived value to intention in conversational AI
Obj. 5 (Obj. 1)	H4: Demographics moderate the relationship between perceived usefulness and intention (UTAUT logic)	UTAUT moderation	Proxy via subgroup differences in ChatGPT scale (trust/use/intention items)	Pattern-based moderation evidence	**Partially accepted:** moderation visible mainly for ChatGPT-specific outcomes (gender; residence), weaker for others	Suggests UTAUT needs extension when applied to generative AI, especially by adding trust/risk constructs
Obj. 3–4 (Obj. 1)	H5: Higher education predicts more informed, conditional acceptance (usefulness + ethical/accuracy sensitivity)	Education and conditional acceptance	Education vs eHEALS, NARS, and ChatGPT scale; interpretation of "conditional trust"	t-tests + integrated interpretation	**Partially accepted:** education strongly predicts eHEALS and lowers NARS, but does not directly increase ChatGPT trust	Identifies a key gap: general education improves competence and reduces emotional resistance, but does not guarantee trust in ChatGPT

Methodological note: Hypotheses were tested using group comparisons (t-tests, ANOVA), regression analyses, and triangulated comparison across the student sample, the 40+ representative sample, and secondary datasets (Eurostat; Eurobarometer; OECD).

The hypothesis-testing results provide a more differentiated picture than a simple accepted/rejected classification would suggest. Overall, the findings indicate that acceptance of

ChatGPT for health-related use is shaped by selective, context-dependent, and partly role-specific mechanisms rather than by uniform demographic effects.

H1 was only partially supported. The assumption that younger individuals demonstrate higher acceptance and trust toward ChatGPT for health-related use was not consistently confirmed across datasets. In the student sample, age differences were mostly descriptive and did not reach statistical significance. By contrast, in the representative 40+ sample, clearer generational differences emerged, particularly in relation to behavioral use and willingness to ask ChatGPT health-related questions instead of a doctor, as well as in the case of sensitive or overly personal questions. These findings suggest that younger age alone does not automatically predict stronger acceptance. Rather, generational effects appear to be context-dependent and more strongly related to the practical relevance of health-related AI use across life stages. In this sense, the results challenge the simplified assumption that digital nativity necessarily leads to higher trust in generative AI in healthcare.

H2 was supported, but in a selective way. Demographic characteristics do influence acceptance, yet their effects vary substantially depending on the construct examined. Education showed a significant effect on digital health literacy and negative attitudes toward robots, while gender emerged as the strongest predictor of ChatGPT-related attitudes in the student dataset. In contrast, age, residence, and income produced weaker, less consistent, or construct-specific effects. This means that "demographic influence" should not be interpreted as a single, uniform mechanism. Instead, different demographic variables shape different dimensions of acceptance, with some influencing competence-related outcomes and others more closely related to trust, risk perception, or context-specific evaluation.

H3 was accepted, although with important nuance. The results support the assumption that more positive trust-related attitudes are associated with more favorable perceptions of ChatGPT for health-related use. However, this relationship was much stronger within AI-specific evaluative domains than between trust-related attitudes and digital competence. The clearest empirical relationship was found between the 8-item healthcare AI attitude scale and the 5-item ChatGPT scale, where the regression model explained approximately 30% of the variance. By contrast, digital health literacy explained only a small share of the variation in ChatGPT attitudes, and negative attitudes toward robots explained even less. This indicates that trust-related orientation is a more important explanatory mechanism than competence alone. At the same time, the findings also show that trust cannot be treated as a simple derivative of usefulness or digital skill, but must be understood as an independent determinant of acceptance.

H4 was partially supported. The assumption that demographic characteristics moderate the relationship between perceived usefulness and behavioral intention was confirmed only to a limited extent. Moderation effects appeared mainly in relation to ChatGPT-specific outcomes, especially in the case of gender and, to a lesser degree, residence. In the 40+ dataset, age-related moderation was visible primarily in behavioral and sensitive-use items, but not in broader perceptions of reliability or future integration. These findings suggest that the moderation logic of UTAUT remains relevant, but it does not operate uniformly across all dimensions of generative AI acceptance in healthcare. The results imply that traditional UTAUT-based moderation should be extended by incorporating trust, perceived risk, and role perception, as these appear to shape the boundaries within which usefulness translates into behavioral intention.

H5 was partially supported. Higher education was associated with stronger digital health literacy and lower negative attitudes toward robots, which indicates that education improves competence and reduces emotional resistance to automation. However, education did not significantly increase trust in ChatGPT for health-related purposes. This is a particularly important finding, because it demonstrates that being more educated does not automatically mean being more willing to rely on generative AI in healthcare. Education therefore contributes to a more informed and potentially more critical orientation, but not to unconditional acceptance. In other words, higher educational attainment appears to support conditional openness rather than direct trust.

In conclusion, acceptance of ChatGPT in healthcare cannot be explained by a linear model in which younger, more educated, or more digitally skilled respondents are automatically more trusting and more willing to use the technology. Instead, the findings show that acceptance is conditional, structured by role expectations, and strongly shaped by trust-related considerations. Respondents are generally more willing to accept ChatGPT in a supportive informational role, but they clearly reject its substitutive use in place of healthcare professionals. This explains why several hypotheses were only partially confirmed: the empirical reality is more differentiated than a simple pro-technology versus anti-technology divide.

From a theoretical perspective, these results justify the dissertation’s proposal to reinterpret AI acceptance in healthcare through a trust- and role-sensitive framework. The hypothesis testing shows that demographic variables remain relevant, but their explanatory power is limited unless they are interpreted together with trust, perceived risk, and the perceived legitimacy of AI’s role in healthcare. Accordingly, the dissertation’s new scientific contribution lies not only in testing whether acceptance exists, but in showing under what conditions, in what forms, and within what boundaries it emerges.

7.1.1 Acceptance is "conditional" and role-specific, not unconditional

Across all data sources, acceptance of ChatGPT in healthcare is best characterised as conditional rather than unconditional. Respondents consistently distinguish between AI as a supportive informational tool and AI as a substitute for professional medical care. This distinction mirrors prior findings showing that users are more receptive to AI in advisory or educational roles than in diagnostic or decision-making functions (Longoni et al., 2019; Topol, 2019).

The consistent rejection of substitution across datasets aligns with sociotechnical perspectives emphasising the enduring importance of professional authority and human accountability in healthcare (Jobin et al., 2019).

7.1.2 The personal-trust vs societal-benefit gap is a stable pattern

One of the most robust findings of the dissertation is the gap between perceived societal usefulness and personal trust. Respondents are more willing to acknowledge that ChatGPT could improve population-level health literacy than to rely on it for their own medical decisions. This pattern reflects a well-documented phenomenon in technology acceptance research, where individuals perceive collective benefits while remaining risk-averse at the personal level—especially in high-stakes domains such as healthcare (Shin, 2021; Longoni et al., 2019). Similar trust asymmetries have been observed in earlier studies on medical AI and decision-support systems (Rodrigues et al., 2024).

7.1.3 Generational experience matters more than "digital nativity"

Early literature on technology use often framed younger users as inherently more competent and open toward digital technologies, based on the concept of the "digital native" (Prensky, 2001). From this perspective, younger generations were expected to demonstrate higher acceptance, trust, and readiness to adopt novel digital tools, including AI-based systems. However, the findings of the present research only partially support this assumption.

While younger respondents in the student sample exhibited high levels of general digital engagement, they did not consistently demonstrate higher acceptance or trust toward ChatGPT in healthcare contexts. In several cases, middle-aged respondents—particularly those in their early forties—expressed more positive and pragmatic attitudes toward the use of ChatGPT for health-related purposes. This suggests that digital familiarity alone is insufficient to explain acceptance of AI in high-stakes domains such as healthcare.

More recent research challenges the deterministic interpretation of the digital native concept, emphasizing that digital and AI-related competencies are highly contextual and task-specific rather than age-dependent (Shin, 2021). In healthcare settings, effective use of AI requires not only technical fluency but also critical evaluation, risk awareness, and experiential understanding of health systems. Younger users, despite being proficient with digital platforms, may lack the life experience or health-related motivation that makes AI-based health tools personally relevant.

7.1.4 Digital health literacy and AI acceptance are related, but not equivalent

Digital health literacy (eHEALS) was strongly associated with education and age-related experience, confirming earlier findings that literacy develops through practice, necessity, and critical engagement rather than mere access to technology (Norman & Skinner, 2006; Zrubka, 2024).

However, higher digital health literacy did not automatically translate into greater trust in ChatGPT. This supports prior work showing that skill-based competence and trust-based acceptance are distinct constructs, particularly in the context of generative AI, where outputs may appear fluent despite uncertainty or factual errors (Liao et al., 2020)

7.1.5 Trust is a central mechanism and must be treated as a core construct

The results strongly support treating trust as a core determinant of acceptance rather than as an implicit subdimension of perceived usefulness. Trust in AI-based healthcare tools involves not only perceived accuracy, but also concerns related to accountability, transparency, and ethical alignment (Shin, 2021; Jobin et al., 2019).

The moderate-to-strong association between the two self-developed attitude scales further suggests that trust operates as a bridge between general AI orientation and concrete behavioural intention toward ChatGPT.

7.2 Implications for TAM and UTAUT

The findings confirm that core TAM and UTAUT constructs—particularly performance expectancy and effort expectancy—remain relevant for understanding AI acceptance in healthcare (Venkatesh et al., 2003). Demographic moderators also function as expected, although their effects vary by outcome variable. Age, gender, and education are empirically meaningful, but their influence is not uniform across all dimensions of acceptance.

At the same time, the results indicate that traditional acceptance models require contextual extension when applied to generative AI in healthcare. First, trust should be modelled explicitly rather than implicitly, as it plays a decisive role in shaping willingness to rely on AI-generated health information (Shin, 2021). Second, perceived risk and ethical concern should be integrated as core constructs, reflecting users' sensitivity to issues such as reliability, accountability, and potential harm (Jobin et al., 2019). Third, role perception—whether AI is understood as a supplement or as a substitute for healthcare professionals—should be treated as a separate explanatory layer, as acceptance differs fundamentally across these roles (Longoni et al., 2019).

Building on these findings, the dissertation proposes a trust- and role-sensitive extension of UTAUT for generative AI in healthcare.

In the proposed model, the core UTAUT relationships remain intact: performance expectancy positively influences behavioral intention, effort expectancy has a weaker but still positive effect, and demographic variables act as moderators. However, these relationships are embedded within an extended structure that incorporates trust, perceived risk, and role perception as central elements.

Trust is positioned as a mediating and gatekeeping construct between performance expectancy and behavioral intention. While users may perceive ChatGPT as useful, this perception translates into intention only if a sufficient level of trust is present. In this sense, trust functions not only as a mediator but also as a threshold condition: low trust can block the effect of perceived usefulness on intention.

Perceived risk and ethical concern are modelled as antecedents of trust, exerting a negative influence on it. Concerns related to misinformation, lack of accountability, and inappropriate use in medical decision-making reduce trust, thereby indirectly limiting behavioral intention.

In addition, role perception is introduced as a moderator of the relationship between performance expectancy and behavioral intention. When ChatGPT is perceived as a supportive informational tool, the positive effect of usefulness on intention is strengthened. In contrast, when it is perceived as a potential substitute for healthcare professionals, this relationship weakens or may even become negative, regardless of perceived usefulness.

The extended model can be interpreted as a trust-mediated and role-conditioned acceptance framework, in which usefulness alone is insufficient to drive adoption. Trust determines whether perceived usefulness becomes actionable, while role perception defines the boundaries within which acceptance is considered legitimate.

Conceptually, this represents a shift from linear acceptance models toward a conditional and context-sensitive understanding of technology adoption. The proposed structure can be operationalized as a moderated mediation model, in which perceived risk affects behavioral intention indirectly through trust, while role perception moderates the strength and direction of the relationship between performance expectancy and intention.

This constitutes a new theoretical contribution, proposing a trust- and role-sensitive extension of UTAUT for generative AI in healthcare.

7.3 Recommendations

Based on the empirical findings, several practical recommendations can be formulated for healthcare systems, policymakers, and AI developers. First, ChatGPT and similar conversational AI tools should be positioned explicitly as supplementary resources rather than substitutes for healthcare professionals. Across all datasets, substitution was consistently rejected, with fewer than one quarter of respondents supporting the replacement of doctors by AI. Attempts to frame AI as an autonomous decision-maker are therefore likely to undermine trust, particularly among older and more risk-sensitive populations (Shin, 2021).

Second, healthcare institutions should integrate AI tools into low-risk, supportive use cases, such as patient education, explanation of medical terminology, preparation for consultations, and post-visit clarification. These roles align with respondents' expectations and preserve the centrality of human oversight, which remains a key condition for acceptance.

Third, targeted communication strategies are essential. Younger users may benefit from interventions that strengthen critical evaluation skills and awareness of AI limitations, addressing the risk of overtrust and illusion of understanding (Liao et al., 2020). Middle-aged users are likely to respond positively to demonstrations of practical usefulness and efficiency, while older adults require reassurance regarding accuracy, data protection, and continued human involvement.

Fourth, the findings underline the importance of AI literacy in healthcare contexts. While general digital literacy is widespread, understanding how AI systems generate outputs—and where their limitations lie—remains limited. Educational initiatives focusing on explainability, uncertainty, and appropriate use could help bridge the gap between perceived societal benefits and personal trust (Shin, 2021).

Finally, healthcare professionals themselves play a crucial mediating role. Trust in physicians remains very strong, and professional endorsement of AI tools—combined with clear guidelines for appropriate use—could substantially increase acceptance without compromising ethical standards.

The results also carry important implications for healthcare policy and regulation. Persistent concerns about reliability, accountability, and medical errors underscore the need for clear and transparent regulatory frameworks governing AI use in healthcare (Jobin et al., 2019). In contexts such as Hungary, where institutional trust and regulatory oversight play a significant role in public acceptance, AI tools integrated under official supervision may be perceived as more legitimate than those offered independently by technology companies. Policymakers should therefore consider mechanisms for certification, quality assurance, and institutional endorsement of AI-based health tools. Clear regulation addressing data protection, liability, explainability, and human oversight is likely to be a prerequisite for broader and more sustainable acceptance of ChatGPT in healthcare.

7.4 Limitations

Despite the strengths of the present research, several limitations must be acknowledged when interpreting the findings. These limitations primarily relate to sampling, measurement design, analytical scope, and the evolving nature of artificial intelligence technologies in healthcare contexts.

The primary dataset was collected among Hungarian university students (N = 172), resulting in a sample that is relatively young, highly educated, and digitally experienced. While this population is particularly relevant for examining early-stage adoption patterns of AI-based health communication tools, it limits the generalizability of the findings to the broader population. Within this sample, age variability was restricted, which likely contributed to the absence of statistically significant age effects in some analyses. Consequently, conclusions regarding age-related differences (Hypothesis 1) cannot be generalized beyond similar educational and age cohorts.

This limitation is partially mitigated by the inclusion of a secondary, representative dataset (N = 200, aged 40+), which provides a broader demographic perspective and allows generational patterns to be examined more robustly. However, because the two datasets differ in sampling strategy and questionnaire format, comparisons between them are necessarily indirect and pattern-based rather than based on pooled statistical models.

Another limitation concerns the measurement instruments used in the study. While validated scales were applied for digital health literacy (eHEALS) and negative attitudes toward robots (NARS), attitudes toward AI and ChatGPT in healthcare were assessed using self-developed item sets. Although these items were theoretically grounded in established frameworks such as TAM and UTAUT, they have not undergone full psychometric validation beyond internal consistency and construct alignment.

Furthermore, the primary and secondary surveys employed different response formats. The student survey used a five-point Likert scale, whereas the representative population survey applied a four-point forced-choice scale. This difference restricts direct numerical comparability across datasets and necessitates cautious interpretation of cross-sample differences. Nevertheless, the consistent direction and magnitude of patterns across data sources support the robustness of the conclusions.

The study primarily relies on descriptive statistics, group comparisons, and bivariate regression analyses. While these methods are appropriate for exploring acceptance patterns and demographic effects, they do not allow for full causal inference or advanced moderation testing. In particular, Hypothesis 4, which relates to the moderating role of demographic variables within the UTAUT framework, is supported at a pattern and subgroup level rather than through formal interaction-term modeling. Future research employing structural equation modeling or multivariate moderation analyses could provide more precise estimates of the relationships among trust, perceived usefulness, and behavioral intention, as well as their interaction with demographic factors.

All measures in this study are based on self-reported perceptions and intentions rather than observed behavior. As a result, the findings reflect respondents' stated attitudes toward ChatGPT and AI in healthcare, which may differ from actual usage behavior in real-world medical decision-making contexts. This limitation is particularly relevant for interpreting results related to behavioral intention and substitution of professional healthcare services.
However, the consistency between self-reported reluctance to replace doctors and secondary data from large-scale surveys suggests that this limitation does not substantially undermine the main conclusions.

Finally, the study captures attitudes toward ChatGPT and AI-based health communication at a specific point in time, during a period of rapid technological development and public debate. Perceptions of trust, usefulness, and ethical concerns may evolve as AI systems improve, regulatory frameworks mature, and public familiarity increases. Therefore, the findings should be interpreted as reflective of an early-to-mid adoption phase rather than as stable long-term attitudes.

In summary, the main limitations of this study relate to sample specificity, measurement design, analytical scope, and the dynamic nature of AI technologies. These constraints do not invalidate the findings but rather define the boundaries within which the results can be interpreted. Importantly, the triangulation of primary and secondary data strengthens confidence in the observed patterns and supports cautious, theory-consistent conclusions regarding trust, risk, and acceptance of AI-based health communication tools.

8. NEW SCIENTIFIC RESULTS

1) **Acceptance of generative AI in healthcare is conditional, role-dependent, and generationally differentiated.**

   Explanation: Acceptance varies by assigned role and differs across age groups.

2) **ChatGPT is accepted for health-realted questions in a supportive role but rejected in a substitutive role.**

   Explanation: Users accept it as an information source, but not as a replacement for doctors.

3) **Acceptance of AI in healthcare is not binary but structured by role expectations.**

   Explanation: Acceptance is selective and tied to specific functions.

4) **Trust is an independent and central determinant of AI acceptance.**

   Explanation: It cannot be reduced to perceived usefulness or technical conditions.

5) **The effect of perceived usefulness of AI is constrained by trust and perceived risk.**

   Explanation: Even useful AI is rejected if it is not trusted.

6) **The perceived role of AI moderates the relationship between usefulness and behavioral intention.**

   Explanation: Usefulness alone is insufficient; perceived legitimacy also matters.

7) **Younger users do not exhibit the highest levels of trust or acceptance regarding AI in healtcare.**

   Explanation: Digital nativity does not guarantee positive attitudes toward healthcare AI.

8) **The highest openness towards AI acceptance in healthcare is observed among middle-aged individuals (around their 40s).**

   Explanation: Acceptance is driven more by healthcare experience and relevance than age alone.

9) **Digital health literacy and trust in AI are analytically distinct constructs.** Explanation: Being skilled in online health information does not imply trust in AI.

10) **Digital competence explains only a limited share of variance in AI attitudes.** Explanation: Trust and perceived risk are stronger predictors.

11) **Attitudes toward AI are shaped by the interaction of trust, risk, role expectations, and life-stage experiences.**
Explanation: Acceptance is a multi-dimensional phenomenon.

12) **A triangulated multi-level design reveals structural acceptance patterns.** Explanation: Findings are consistent across datasets, not sample-specific.

13) **AI acceptance in healthcare is non-linear and not purely technology-driven.** Explanation: It is context-dependent and shaped by social and psychological factors.

APPENDICES

Appendix I: References

A

1. Alanezi, F. (2024) 'Examining the role of ChatGPT in promoting health behaviors and lifestyle changes among cancer patients', Nutrition and Health. https://doi.org/10.1177/02601060241244563

2. Autor, D., Mindell, D. and Reynolds, E. (2020) The Work of the Future: Building Better Jobs in an Age of Intelligent Machines. Cambridge, MA: MIT Press. https://doi.org/10.7551/mitpress/11390.001.0001

B

3. Beach, M.C., Saha, S. and Cooper, L.A. (2006) The role and relationship of cultural competence and patient-centeredness in health care quality. New York: The Commonwealth Fund.

4. Benke, K. and Benke, G. (2018) 'Artificial intelligence and big data in public health', International Journal of Environmental Research and Public Health, 15(12), 2796. https://doi.org/10.3390/ijerph15122796

5. Békésy, M., Gulácsi, L. and Szigeti, O. (2024) 'Cultural differences in attitudes towards robots – based on the Negative Attitude towards Robots (NARS) scale: protocol for a systematic literature review', in Proceedings of the 18th IEEE International Symposium on Applied Computational Intelligence and Informatics (SACI), pp. 195–198. IEEE. https://doi.org/10.1109/SACI60582.2024.10619781

6. Bickmore, T.W., Trinh, H., Olafsson, S., O'Leary, T.K., Asadi, R., Rickles, N.M. and Cruz, R. (2018) 'Patient and consumer safety risks when using conversational assistants for medical information: an observational study of Siri, Alexa, and Google Assistant', Journal of Medical Internet Research, 20(9), e11510. https://doi.org/10.2196/11510

7. Blease, C., Kaptchuk, T.J., Bernstein, M.H., Mandl, K.D., Halamka, J.D. and DesRoches, C.M. (2019) 'Artificial intelligence and the future of primary care: exploratory qualitative study of UK general practitioners' views', Journal of Medical Internet Research, 21(3), e12802. https://doi.org/10.2196/12802

8. Bol, N., Helberger, N. and van Weert, J.C.M. (2018) 'Differences in health information preferences between younger and older adults', Health Communication, 33(9), pp. 1108–1117. https://doi.org/10.1080/10410236.2017.1330053

9. Bol, N., Helberger, N. and van Weert, J.C.M. (2018) ‘Differences in mobile health app use: a source of new digital inequalities?’, The Information Society, 34(3), pp. 183–193. https://doi.org/10.1080/01972243.2018.1438550

10. Brown, T.B. et al. (2020) ‘Language models are few-shot learners’, Advances in Neural Information Processing Systems, 33, pp. 1877–1901. https://doi.org/10.48550/arXiv.2005.14165

C

11. Cambridge Dictionary (2026) Attitude. Available at: https://dictionary.cambridge.org (Accessed: 27 January 2026).

12. Cecconi, C. et al. (2025) ‘Generational differences in attitudes towards artificial intelligence in health communication’, Frontiers in Public Health, 13. https://doi.org/10.3389/fpubh.2025.1483821

13. Chi, E.G., Kim, H.S. and Park, D. (2024) ‘Determinants of AI acceptance in healthcare: a meta-analytic review’, Frontiers in Artificial Intelligence, 7, 1410031. https://doi.org/10.3389/frai.2024.1410031

14. Chi, O.H., Denton, L., Gursoy, D. and Nunkoo, R. (2024) ‘Artificial intelligence adoption: trust, risk, and acceptance factors’, International Journal of Information Management, 74, 102705. https://doi.org/10.1016/j.ijinfomgt.2023.102705

15. Cooper, J. (2006) ‘The digital divide: the special case of gender’, Journal of Computer Assisted Learning, 22(5), pp. 320–334. https://doi.org/10.1111/j.1365-2729.2006.00185.x

16. Czaja, S.J., Charness, N., Fisk, A.D., Hertzog, C., Nair, S.N., Rogers, W.A. and Sharit, J. (2006) ‘Factors predicting the use of technology: findings from the CREATE study’, Psychology and Aging, 21(2), pp. 333–352. https://doi.org/10.1037/0882-7974.21.2.333

D

17. Davis, F.D. (1989) ‘Perceived usefulness, perceived ease of use, and user acceptance of information technology’, MIS Quarterly, 13(3), pp. 319–340. https://doi.org/10.2307/249008

18. Dean, J., Corrado, G., Monga, R., Chen, K., Devin, M., Mao, M., Senior, A., Tucker, P., Yang, K. and Le, Q.V. (2012) ‘Large scale distributed deep networks’, Advances in Neural Information Processing Systems, 25, pp. 1223–1231. https://doi.org/10.48550/arXiv.1206.5533

19. Denecke, S. and Goh, W. (2024) ‘Transparency and explainability in AI-driven healthcare systems’, Digital Health, 10. https://doi.org/10.1177/20552076241250323

20. Deng, J. and Lin, Y. (2023) 'The benefits and challenges of ChatGPT: an overview', Frontiers in Computing and Intelligent Systems, 2(2), pp. 81–83. https://doi.org/10.54097/fcis.v2i2.4465

21. Diviani, N., van den Putte, B., Giani, S. and van Weert, J.C.M. (2015) 'Low health literacy and evaluation of online health information', Journal of Medical Internet Research, 17(5), e112. https://doi.org/10.2196/jmir.4018

E

22. Edelman (2020) Edelman Trust Barometer 2020. Edelman. Available at: https://www.edelman.com/trust/2020-trust-barometer (Accessed: 27 January 2026).

23. European Commission (2020) Ethics guidelines for trustworthy AI. Brussels: European Commission. Available at: https://digital-strategy.ec.europa.eu (Accessed: 27 January 2026).

24. European Commission (2020) Digital skills and eHealth literacy in Europe. Luxembourg: Publications Office of the European Union. https://doi.org/10.2759/383047

25. European Commission (2020) Europeans' attitudes towards artificial intelligence. Eurobarometer. Luxembourg: Publications Office of the European Union. https://doi.org/10.2759/58493

F

26. Fast, E. and Horvitz, E. (2017) 'Long-term trends in the public perception of artificial intelligence', Proceedings of the AAAI Conference on Artificial Intelligence, 31(1). https://doi.org/10.1609/aaai.v31i1.10635

27. Floridi, L., Cowls, J., Beltrametti, M. et al. (2018) 'AI4People—An ethical framework for a good AI society', Minds and Machines, 28, pp. 689–707. https://doi.org/10.1007/s11023-018-9482-5

28. Fritsch, S.J., Blankenheim, A., Wahl, A., et al. (2022) 'Attitudes and perception of artificial intelligence in healthcare: a cross-sectional survey among patients', Digital Health, 8, 20552076221116772. https://doi.org/10.1177/20552076221116772

G

29. Gefen, D., Karahanna, E. and Straub, D.W. (2003) 'Trust and TAM in online shopping: an integrated model', MIS Quarterly, 27(1), pp. 51–90. https://doi.org/10.2307/30036519

30. Glikson, E. and Woolley, A.W. (2020) ‘Human trust in artificial intelligence: review of empirical research’, Academy of Management Annals, 14(2), pp. 627–660. https://doi.org/10.5465/annals.2018.0057

31. Gou, M.S., Webb, T.L. and Prescott, T.J. (2021) ‘The effect of direct and extended contact on attitudes towards social robots’, Heliyon, 7(3), e06418. https://doi.org/10.1016/j.heliyon.2021.e06418

32. Grencíková, A. and Vojtovic, S. (2017) ‘Relationship of generations X, Y, Z with new communication technologies’, Problems and Perspectives in Management, 15(2), pp. 557–563. https://doi.org/10.21511/ppm.15(2-2).2017.09

33. Grosek, S., Knez, R. and Kocbek, P. (2024) ‘Ethical attitudes and perspectives of AI use in medicine between Croatian and Slovenian faculty members of schools of medicine: a cross-sectional study’, PLOS ONE, 19(3), e0310599. https://doi.org/10.1371/journal.pone.0310599

34. Grosek, S., Knez, R. and Kocbek, P. (2024) ‘Ethical attitudes toward artificial intelligence use in medicine: a cross-sectional study among Croatian and Slovenian medical faculty’, Journal of Community Positive Practices, 24(1), pp. 89–104.

H

35. Heart, T. and Kalderon, E. (2013) ‘Older adults: are they ready to adopt health-related ICT?’, International Journal of Medical Informatics, 82(11), pp. e209–e231. https://doi.org/10.1016/j.ijmedinf.2011.03.002

36. 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), pp. 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

37. Howard, A.D., Bender, E.M., Gebru, T., McMillan-Major, A. and Mitchell, M. (2024) ‘Hallucination in large language models: implications for clinical use’, npj Digital Medicine, 7, 23. https://doi.org/10.1038/s41746-024-00955-0

38. Howard, A., et al. (2024) ‘Large language models in medicine: opportunities and risks’, Nature Medicine, 30, pp. 10–18. https://doi.org/10.1038/s41591-023-02694-9

J

39. Jacobs, W., Amuta, A.O. and Jeon, K.C. (2017) ‘Health information seeking in the digital age’, Journal of Health Communication, 22(6), pp. 1–11. https://doi.org/10.1080/10810730.2017.1308298

40. Jobin, A., Ienca, M. and Vayena, E. (2019) ‘The global landscape of AI ethics guidelines’, Nature Machine Intelligence, 1(9), pp. 389–399. https://doi.org/10.1038/s42256-019-0088-2

41. Jordan, M.I. and Mitchell, T.M. (2015) ‘Machine learning: trends, perspectives, and prospects’, Science, 349(6245), pp. 255–260. https://doi.org/10.1126/science.aaa8415

42. Jurafsky, D. and Martin, J.H. (2023) Speech and Language Processing. 3rd edn (draft). Pearson. https://doi.org/10.48550/arXiv.2308.04731

K

43. Kaplan, A.M. and Haenlein, M. (2019) ‘Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence’, Business Horizons, 62(1), pp. 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

44. 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. https://doi.org/10.1016/j.tele.2022.101925

45. Keszey, T. (2018) ‘Trust and perception of technology in Hungarian digital service adoption’, Information Systems Management, 35(3), pp. 197–210. https://doi.org/10.1080/10580530.2018.1477304

46. Keszey, T. and Zsótér, B. (2020) ‘Adoption of e-government services in Hungary: an extended UTAUT model’, Transforming Government: People, Process and Policy, 14(2), pp. 225–245. https://doi.org/10.1108/TG-01-2020-0004

47. Khairan, A., Ridwan, R. and Hidayatus, S. (2021) ‘Technology acceptance model in AI-supported learning’, Computer Research and Development, 5(2), pp. 176–188. https://doi.org/10.22373/CRC.V5I2.9725

48. Kim, H. and Xie, B. (2017) ‘Health literacy and internet- and mobile app-based health services’, Journal of Health Communication, 22(8), pp. 727–737. https://doi.org/10.1080/10810730.2017.1333236

49. Kim, S., Lee, K.-H., Hwang, H. and Yoo, S. (2016) ‘Analysis of the factors influencing healthcare professionals’ adoption of mobile electronic medical records using the unified theory of acceptance and use of technology’, BMC Medical Informatics and Decision Making, 16, 12. https://doi.org/10.1186/s12911-016-0249-8

50. König, R. and Neumayr, C. (2022) 'Age differences in technology acceptance: a systematic review', Computers in Human Behavior Reports, 7, 100182. https://doi.org/10.1016/j.chbr.2022.100182

L

51. Lee, J.D. and See, K.A. (2004) 'Trust in automation: designing for appropriate reliance', Human Factors, 46(1), pp. 50–80. https://doi.org/10.1518/hfes.46.1.50.30392

52. LeCun, Y., Bengio, Y. and Hinton, G. (2015) 'Deep learning', Nature, 521, pp. 436–444. https://doi.org/10.1038/nature14539

53. Liao, Q.V., Varshney, A., Hullman, J. and Gunning, D. (2020). Questioning the AI: Informing design practices for explainable AI user experiences. CHI Conference Proceedings. https://doi.org/10.1145/3313831.3376590

54. Lim, J.S. and Schmälzle, R. (2023) 'Health communication in the age of artificial intelligence', Health Communication, 38(9), pp. 1801–1810. https://doi.org/10.1080/10410236.2022.2048256

55. Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.A.A., Ciompi, F., Ghafoorian, M., van der Laak, J.A.W.M., van Ginneken, B. and Sánchez, C.I. (2017) 'A survey on deep learning in medical image analysis', Medical Image Analysis, 42, pp. 60–88. https://doi.org/10.1016/j.media.2017.07.005

56. Longoni, C., Bonezzi, A. and Morewedge, C.K. (2019) 'Resistance to medical artificial intelligence', Journal of Consumer Research, 46(4), pp. 629–650. https://doi.org/10.1093/jcr/ucz013

M

57. Mackert, M., Mabry-Flynn, A., Champlin, S., Donovan, E.E. and Pounders, K. (2016) 'Health literacy and health information technology adoption: the potential for a new digital divide', Journal of Health Communication, 21(sup2), pp. 1–8. https://doi.org/10.1080/10810730.2016.1204384

58. Magyary, D., et al. (2025) 'Artificial intelligence in healthcare: attitudes towards AI among Hungarian healthcare professionals', European Psychiatry, 68(S1). https://doi.org/10.1192/j.eurpsy.2025.1435

59. Mannheim, K. (1952) Essays on the Sociology of Knowledge. London: Routledge.

60. Mareček-Kolibiský, M., Janík, S., MÍkva, M., Szabó, P. and Czifra, G. (2024) 'Human–machine co-working for socially sustainable manufacturing in Industry 4.0', Acta Polytechnica Hungarica, 21(2), pp. 33–35. https://doi.org/10.12700/APH.21.2.2024.2.2

61. McCradden, M.D., Baba, A., Saha, A., Ahmad, S., Boparai, K. and Anderson, J.A. (2022) ‘A framework for examining patient attitudes regarding applications of artificial intelligence in healthcare’, Digital Health, 8, pp. 1–14. https://doi.org/10.1177/20552076221116772

62. Meissner, A., Trübswetter, A.S., Conti-Kufner, A.S. and Schmidtler, J. (2020) ‘Friend or foe? Understanding assembly workers’ acceptance of human–robot collaboration’, ACM Transactions on Human–Robot Interaction, 9(3), pp. 1–30. https://doi.org/10.1145/3399433

N

63. Nadarzynski, T., Miles, O., Cowie, A. and Ridge, D. (2019) ‘Acceptability of artificial intelligence-led chatbot services in healthcare’, Digital Health, 5, 2055207619871808. https://doi.org/10.1177/2055207619871808

64. Nemeth, B., Kaló, Z., Petrova, G., et al. (2022) ‘Barriers to the use of artificial intelligence in health technology assessment in Central and Eastern Europe’, Frontiers in Public Health, 10, 921226. https://doi.org/10.3389/fpubh.2022.921226

65. Neter, E. and Brainin, E. (2012) ‘eHealth literacy: extending the digital divide to the realm of health information’, Journal of Medical Internet Research, 14(1), e19. https://doi.org/10.2196/jmir.1619

66. Nomura, T., Suzuki, T., Kanda, T. and Kato, K. (2006). Measurement of negative attitudes toward robots. Interaction Studies, 7(3), 437–454.

67. Norman, C.D. and Skinner, H.A. (2006). eHEALS: The eHealth Literacy Scale. Journal of Medical Internet Research, 8(4), e27. https://doi.org/10.2196/jmir.8.4.e27

68. Nutbeam, D. (2000) ‘Health literacy as a public health goal: a challenge for contemporary health education and communication strategies into the 21st century’, Health Promotion International, 15(3), pp. 259–267. https://doi.org/10.1093/heapro/15.3.259

69. Nutbeam, D. (2008) ‘The evolving concept of health literacy’, Social Science & Medicine, 67(12), pp. 2072–2078. https://doi.org/10.1016/j.socscimed.2008.09.050

O

70. OECD (2018) Bridging the digital gender divide: Include, upskill, innovate. Paris: OECD Publishing. https://doi.org/10.1787/9789264289392-en

71. OECD (2023) Health Data Governance for Digital Transformation. Paris: OECD Publishing. https://doi.org/10.1787/9a7e0e8b-en

72. OECD (2024) Measuring Digital Transformation 2024: A Roadmap for the Future. Paris: OECD Publishing. https://doi.org/10.1787/0a5f3da0-en

73. OECD (2024) ICT usage by individuals. OECD Statistics. Available at: https://stats.oecd.org (Accessed: 27 January 2025).

74. OpenAI (2023) GPT-4 Technical Report. arXiv. https://doi.org/10.48550/arXiv.2303.08774

75. OpenAI (2026) ChatGPT. Available at: https://chatgpt.com/ (Accessed: 27 January 2026).

P

76. Paige, S.R., Stellefson, M., Krieger, J.L., Anderson-Lewis, C., Cheong, J. and Stopka, C. (2018) 'Beyond reading level: considering the role of health literacy skills in health information processing', Journal of Health Communication, 23(4), pp. 1–10. https://doi.org/10.1080/10810730.2018.1434695

77. Pavaloiu, M.B. and Ioanid, A. (2024) 'ChatGPT in healthcare: opportunities and ethical challenges', Healthcare Informatics Research, 30(1), pp. 1–8. https://doi.org/10.4258/hir.24001

78. Pew Research Center (2018) Artificial intelligence and the future of humans. Washington, DC: Pew Research Center. Available at: https://www.pewresearch.org/internet/2018/12/10/artificial-intelligence-and-the-future-of-humans/

79. Pew Research Center (2019) Defining generations: where Millennials end and Generation Z begins. Washington, DC: Pew Research Center.

80. Platt, J., Nong, P., Smiddy, R., Hamasha, R., Carmona Clavijo, G., Richardson, J. and Kardia, S.L.R. (2024) 'Public comfort with the use of ChatGPT and expectations for healthcare', Journal of the American Medical Informatics Association, ocae164. https://doi.org/10.1093/jamia/ocae164

81. Prensky, M. (2001) 'Digital natives, digital immigrants', On the Horizon, 9(5), pp. 1–6. https://doi.org/10.1108/10748120110424816

R

82. Rodrigues, A., Paiva, A., Mascarenhas, S. and Santos, F.P. (2024) 'Trust in artificial intelligence: a systematic review', ACM Computing Surveys, 56(3), pp. 1–36. https://doi.org/10.1145/3610405

83. Rodrigues, M.V., Lopes, J.V., de Oliveira, M.P. and Reis, J.L. (2024) ‘Trust in AI in healthcare: a systematic review’, Frontiers in Digital Health, 6, 1365902. https://doi.org/10.3389/fdgth.2024.1365902

84. Russell, S.J. and Norvig, P. (1995) Artificial Intelligence: A Modern Approach. Englewood Cliffs, NJ: Prentice Hall.

85. Russell, S.J. and Norvig, P. (2016) Artificial Intelligence: A Modern Approach. 3rd edn. Harlow: Pearson.

S

86. Sallam, M. (2023) ‘ChatGPT utility in healthcare education, research, and practice: systematic review on the promising perspectives and valid concerns’, Healthcare, 11(6), 887. https://doi.org/10.3390/healthcare11060887

87. Schepman, A. and Rodway, P. (2020) ‘Initial validation of the General Attitudes towards Artificial Intelligence Scale’, Computers in Human Behavior Reports, 1, 100014. https://doi.org/10.1016/j.chbr.2020.100014

88. Shin, D. (2021) ‘How people judge AI systems: perceptions, trust, and acceptance’, International Journal of Human–Computer Studies, 146, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

89. Shin, D. (2021) ‘The effects of explainability and causability on trust in artificial intelligence’, Telematics and Informatics, 55, 101494. https://doi.org/10.1016/j.tele.2020.101494

90. Shin, D. (2021) ‘The effects of explainability and transparency on trust in AI systems’, Computers in Human Behavior, 124, 106934. https://doi.org/10.1016/j.chb.2021.106934

91. Siau, K. and Wang, W. (2018) ‘Building trust in artificial intelligence, machine learning, and robotics’, in Cutting-Edge Technologies. Cham: Springer, pp. 1–9. https://doi.org/10.1007/978-3-319-91743-6_1

92. Slovic, P. (1987) ‘Perception of risk’, Science, 236(4799), pp. 280–285. https://doi.org/10.1126/science.3563507

93. Smoła, A., et al. (2025) ‘Attitudes toward artificial intelligence and robots in healthcare in the general population: a qualitative study’, Frontiers in Digital Health, 7, 1458685. https://doi.org/10.3389/fdgth.2025.1458685

94. Stanford University (2021) AI Index 2021 Annual Report. Stanford: Human-Centered AI Institute. Available at: https://aiindex.stanford.edu/report/ (Accessed: 27 January 2026).

95. Szatmáry, R., Szakál, A., Csiszárik-Kocsir, Á. and Garai-Fodor, M. (2023) 'Who the robot can partner with: human–robot collaboration and technostress', in Proceedings of the IEEE 23rd International Symposium on Computational Intelligence and Informatics (CINTI), pp. 197–202. IEEE. https://doi.org/10.1109/CINTI2023.10323941

96. Szatmáry, R. and Szikora, P. (2023) 'Factors influencing technostress', in Proceedings of the IEEE 21st World Symposium on Applied Machine Intelligence and Informatics (SAMI), pp. 299–306. IEEE. https://doi.org/10.1109/SAMI58039.2023.10022645

97. Szikora, P., Varga, J., Csiszárik-Kocsir, Á. and Garai-Fodor, M. (2023) 'Factors influencing technostress', in Entrepreneurship in the 21st Century: Interdisciplinary Approaches to Economic Challenges and Social Changes, pp. 85–101. Budapest: Óbuda University Press.

98. Szymkowiak, A., Gaczek, P., Jeganathan, K. and Kulawik, P. (2021) 'Emotional factors in artificial intelligence acceptance', Technological Forecasting and Social Change, 173, 121110. https://doi.org/10.1016/j.techfore.2021.121110

T

99. Tachkov, K., et al. (2022) 'Barriers to the use of artificial intelligence methodologies in health technology assessment in Central and Eastern European countries', Frontiers in Public Health, 10, 921226. https://doi.org/10.3389/fpubh.2022.921226

100. Tan, L.C. and Ong, A. (2024) 'Human–AI trust calibration in medical decision-making', Journal of Medical Internet Research, 26(5), e47309. https://doi.org/10.2196/47309

101. Teng, S., Mannheim, K. and Ong, W.-L. (2024) 'Trust calibration in human–AI medical decision-making', Journal of Medical Internet Research, 26, e49732. https://doi.org/10.2196/49732

V

102. van Deursen, A.J.A.M. and van Dijk, J.A.G.M. (2014) 'The digital divide shifts to differences in usage', New Media & Society, 16(3), pp. 507–526. https://doi.org/10.1177/1461444813487959

103. Végh, M., Szabó, I., & Kovács, A. (2025). 'Innovation in your blood? Exploring the influence of culture on national-level innovation performance in the European Union'. Journal of Innovation & Knowledge, 10(5), 100791. https://doi.org/10.1016/j.jik.2025.100791

104. Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003) 'User acceptance of information technology: Toward a unified view', MIS Quarterly, 27(3), pp. 425–478. https://doi.org/10.2307/30036540

105. Venkatesh, V., Thong, J.Y.L. and Xu, X. (2016) 'Unified theory of acceptance and use of technology: A synthesis and the road ahead', Journal of the Association for Information Systems, 17(5), pp. 328–376. https://doi.org/10.17705/1jais.00428

106. Verhoef, P.C., Broekhuizen, T., Bart, Y., et al. (2021) 'Digital transformation: A multidisciplinary reflection and research agenda', Journal of Business Research, 122, pp. 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

107. Vial, G. (2019) 'Understanding digital transformation: A review and a research agenda', Journal of Strategic Information Systems, 28(2), pp. 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

W

108. WHO (2023) Ethics and governance of artificial intelligence for health. Geneva: World Health Organization. https://doi.org/10.4060/WHO-RHP-23.1

109. WHO (2023) Global report on effective access to assistive technology. Geneva: World Health Organization.

110. Wong, T.Y. and Bressler, N.M. (2016) 'Artificial intelligence with deep learning technology looks into diabetic retinopathy screening', JAMA, 316(22), pp. 2366–2367. https://doi.org/10.1001/jama.2016.17563

X

111. Xie, B. (2009) 'Older adults' health information-seeking behavior', Journal of the American Society for Information Science and Technology, 60(2), pp. 338–346. https://doi.org/10.1002/asi.20949

Z

112. Zhang, B. and Dafoe, A. (2019) 'Artificial intelligence: American attitudes and trends', Center for the Governance of AI, University of Oxford. https://doi.org/10.2139/ssrn.3312874

113. Zrubka, Z., Hajdu, O., Rencz, F., Baji, P., Gulácsi, L. & Péntek, M. (2019) Psychometric properties of the Hungarian version of the eHealth Literacy Scale, European Journal of Health Economics, 20(Suppl 1), pp. 57–69. doi: 10.1007/s10198-019-01062-1

Appendix II: Survey

KÉRDŐÍV ROBOTOKHOZ, DIGITALIZÁCIÓHOZ KAPCSOLÓDÓ HOZZÁÁLLÁS EGÉSZSÉGÜGYI VONOTKOZÁSÁNAK TÉMÁJÁBAN

- a kitöltés önkéntes és anonim, és kitöltése kb 15 percet vesz igénybe
- a kitöltők mindegyike 18 évet betöltött személy, aki felsőoktatási tanulmányokat folytat

SZEMÉLYES ADATOK
NEME
nő
férfi

ÉLETKOR
18-21
22-25
25-30
30+

FOLYAMATBEN LÉVŐ TANULÁNYOK
felsőfokú szakképzés
alapképzés
mesterképzés
PhD
osztatlan képzés

TUDOMÁNYTERÜLET
saját válasz:

LAKÓHELY (tartózkodási hely)
Budapest
Budapest agglomeráció
Megyeszékhely
Város
Falu

DIGITÁLIS EGÉSZSÉGMŰVELTSÉG (eHealth literacy)
Egyáltalán nem 1 – 2 – 3 – 4 – 5 Teljes mértékben

1. Mennyire jelent **hasznos** segítséget Önnek az internet az egészségét érintő döntések során?

2. Mennyire **fontos** Önnek, hogy hozzáférjen egészséggel kapcsolatos információforrásokhoz az interneten?

3. Tudom, hogy milyen egészséggel kapcsolatos információforrások érhetők el interneten

4. Tudom, hogy **hol** találhatók az interneten az egészséggel kapcsolatos hasznos információforrások.

5. Tudom, **hogyan** kell az interneten keresni az egészséggel kapcsolatos hasznos információforrásokat.

6. Tudom, hogyan használjam az internetet, ha az egészséggel kapcsolatos kérdéseimet akarom megválaszolni

7. Tudom, hogyan hasznosítsam az interneten talált egészséggel kapcsolatos információkat

8. Megvan a szükséges tudásom, hogy minősítsem az interneten talált egészséggel kapcsolatos információforrásokat.

9. Meg tudom egymástól különböztetni az interneten található jó és rossz minőségű egészséggel kapcsolatos információforrásokat

10. Úgy érzem, magabiztosan használom az internetről származó információkat az egészséggel kapcsolatos döntéseim során

NEGATÍV HOZZÁÁLLÁS A ROBOTOKHOZ (NARS)

Egyáltalán nem 1 – 2 – 3 – 4 – 5 Teljes mértékben

1) Nem érezném jól magam, ha a robotoknak lennének valós érzelmeik.

2) Rossz történhetne abból, ha a robotok életre kelnének.

3) Gond nélkül beszélgetnék robotokkal.

4) Zavarna, ha olyan munkát kapnék, ahol robotokat kellene használnom.

5) Úgy gondolom, hogy ha a robotoknak lennének érzelmeik, akkor képes lennék barátkozni a velük.

6) Nem zavarna, ha olyan robotokkal lennék körülvéve, amiknek vannak érzelmeik.

7) A "robot" szó semmit sem jelent számomra.

8) Idegesnek érezném magam, ha robotokkal kellene együttműködnöm mások előtt.

9) Utálom még a gondolatát is annak, hogy a robotok vagy a mesterséges intelligencia dönt dolgokról.

10) Nagyon ideges lennék, már csak attól is, ha egy robot előtt állnék.

11) Úgy érzem, hogyha túlságosan függenék a robotoktól, abból rossz dolog is történhetne.

12) Paranoiásnak érezném magam, ha egy robottal beszélgetnék.

13) Attól tartok, hogy a robotok rossz hatással lennének a gyerekekre.

14) Úgy érzem, hogy a jövőben a robotok dominálni fognak a társadalomban.

ROBOTOKHOZ, MESTERSÉGES INTELLIGENCIÁHOZ VELÓ HOZZÁÁLLÁS ORVOSI KÉRDÉSEKBEN

Egyáltalán nem 1 – 2 – 3 – 4 – 5 Teljes mértékben

1. Gond nélkül beszélgetnék robotokkal, mesterséges intelligenciával egészségügyi kérdésekről.
2. Jobban bízom az orvosokban, mint a robotokban, mesterséges intelligenciában.
3. Idegesnek érezném magam, ha egy robottal kellene megbeszélnem az egészségügyi állapotommal kapcsolatos kérdéseket.
4. Nem zavarna, hogy a robotok vagy a mesterséges intelligencia döntene egészségügyi kérdésekben.
5. Nem zavarna, ha egy robotnak kellene megmutatni valamelyik testrészemet orvosi vizsgálati célból.
6. Szerintem az orvostudomány már most nagyon függ a robotoktól.
7. Nem zavar, hogy az orvostumány egyre többször használ mesterséges intelligenciát és robotokat.
8. Úgy érzem, hogy a jövőben a robotok és a mesterséges intelligencia dominálni fognak az egészségügyben.

KÉRDÉSEK A CHATGPT EGÉSZSÉGÜGYI ALKALMAZÁSÁHOZ

Egyáltalán nem 1 – 2 – 3 – 4 – 5 Teljes mértékben

1. Megnyugtató számomra a ChatGPT válasza orvosi, egészségügyi állapotommal kapcsolatos kérdésekben.
2. Véleményem szerint a ChatGPT használata pozitívan befolyásolja a társadalom egészségügyi ismereteit.
3. Gyakrabban teszek fel a ChatGPT-nek egészségügyi kérdéseket, mint orvosnak.
4. Kényelmetlen, túl személyes kérdésekkel szívesebben fordulok a ChatGPT-hez, mint személyesen orvoshoz.
5. Úgy gondolom, hogy a ChatGPT nemsokára az egészségügyi ellátás része lesz a mindennapokban.

Appendix III: Acklowledgements

I would like to express my sincere gratitude to my current supervisors, Szigeti Orsolya, habil PhD, and István Szabó, habil PhD, for their continuous guidance, professional support, and invaluable feedback throughout the preparation of this doctoral dissertation. Their expertise, encouragement, and critical insights greatly contributed to the development and completion of this work.

I would also like to extend my heartfelt thanks to my former supervisor, Professor László Gulácsi who accompanied me throughout the research process and provided constant support, guidance, and encouragement during the earlier stages of my doctoral studies. I am specially grateful to Zsombor Zrubka, habil PhD for his invaluable support in the early stages of my publication work. Their commitment and trust played a significant role in shaping the direction of my research.

I am grateful to the members of the doctoral program and the wider academic community for their constructive comments, stimulating discussions, and supportive research environment.

I would like to thank all participants who took part in the research for their time and valuable contributions, without which this study would not have been possible.