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ARTIFICIAL INTELLIGENCE IN HEALTH-RELATED INFORMATION USE:

A CONSUMER PERSPECTIVE FROM YOUNG ADULTS

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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).

The scientific relevance of the topic is threefold. First, a substantial part of the existing literature examines artificial intelligence in broad or institutional contexts rather than publicly accessible generative AI systems such as ChatGPT (Pavaloiu and Ioanid, 2024; Lim and Schmälzle, 2023). Second, healthcare-related acceptance mechanisms differ from conventional consumer technology contexts because trust, accountability, perceived risk, and information accuracy play a central role in user evaluations (Longoni et al., 2019; Shin, 2021; Howard et al., 2024). Third, empirical evidence from Hungary and the broader Central and Eastern European region remains comparatively limited, despite potentially relevant cultural and institutional differences in trust and technology adoption. Hungary represents a relavant case due to its transitional digital environment, aging population, and growing reliance on online health information (OECD, 2024; Rodrigues et al., 2024).

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 dissertation is to provide a theory-informed empirical examination of public attitudes toward the use of ChatGPT in health-related information seeking, with particular attention to trust, generational differences, and acceptance mechanisms (Rodrigues et al., 2024; Tan and Ong, 2024; Howard et al., 2024). In particular, the dissertation examines whether age- and generational-related differences shape trust and willingness to use AI-based health communication tools.

This dissertation contributes to the literature by integrating trust-based and demographic explanations within a healthcare-specific AI acceptance framework, with particular reference to emerging generative AI systems; and is structured into chapters covering the literature review, hypotheses development, methodology, empirical results, discussion, conclusions, and scientific contributions.

2. AIMS AND OBJECTIVES

The primary aim of this doctoral dissertation is to explain the determinants of public acceptance of ChatGPT for health-related purposes in Hungary, with particular emphasis on trust, demographic characteristics, perceived usefulness, and behavioral intention with particular emphasis on trust, demographic characteristics, perceived usefulness, behavioural intention, and the role-based and trust-sensitive nature of AI acceptance. In doing so, the dissertation seeks to contribute to the broader literature on AI acceptance in high-stakes service environments such as healthcare (Venkatesh et al., 2003; Rodrigues et al., 2024).

In order to contribute to the broader literature on AI acceptance, the dissertation also aims 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). Although UTAUT2 was originally developed for consumer technology adoption contexts and includes constructs such as hedonic motivation, habit, and price value (Venkatesh et al., 2012), the present dissertation primarily examines healthcare-related information seeking, trust formation, and risk-sensitive decision contexts. Moreover, contrsucts such as price value are of limited relevance in the context of freely accessible AI tools such as ChatGPT.

Therefore, the original UTAUT framework provides a more appropriate theoretical baseline due to its stronger emphasis on performance expectancy, effort expectancy, social influence, and demographic moderators. At the same time, selected insights from later model extensions are incorporated where relevant.

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. The originality of the dissertation lies in combining multiple datasets to examine trust- and role-sensitive acceptance of generative AI in healthcare.

Based on the identified research gaps and theoretical considerations discussed above, the present dissertation aims to examine the selected topic in a structured and comprehensive manner. To operationalise these aims, five specific research objectives were formulated:

- **Objective 1**: to synthesise and critically review international literature on AI acceptance in healthcare, with particular attention to generative AI, trust, and conversational systems.
- **Objective 2:** to describe public attitudes toward ChatGPT as a health-related information tool in Hungary, including perceived usefulness, reliability, role perception, and willingness to use.
- **Objective 3**: to examine how demographic background variables (age, gender, education, residence, and income) relate to trust and acceptance, in line with technology acceptance theory (Venkatesh et al., 2003; König and Neumayr, 2022).

– **Objective 4:** to examine the potential gap between digital health literacy and trust in AI-based health tools (Norman and Skinner, 2006; Shin, 2021).

– **Objective 5**: to evaluate the explanatory limitations of TAM and UTAUT frameworks in AI healthcare contexts and to propose a trust- and role-based extension.

Together, these objectives ensure alignment between the theoretical framework, empirical design, and hypothesis testing trategy of the dissertation. These objectives also provide the analytical foundation for the hypotheses developed in Chapter 4.

By combining an university-based sample, a representative 40+ population sample, and secondary statistical indicators, the dissertation applies a triangulated multi-source research design. This approach allows a more robust interpretation of acceptance patterns than single-sample studies and strengthens the empirical basis of the conclusions (OECD, 2024; Eurostat, 2023). The three empirical components are complementary rather than directly comparable.

The integrated conceptual framework of the dissertation is presented in Chapter 3, in the literature review.

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. In contemporary information systems and social science research, artificial intelligence is generally understood as a family of computational systems capable of performing tasks that traditionally require human cognitive abilities, including learning, reasoning, prediction, and language processing (Russell and Norvig, 2016; Floridi et al., 2018). 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). Such systems are increasingly integrated into healthcare environments, while global investment and public exposure to artificial intelligence technologies continue to grow rapidly (Stanford University, 2021).

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).

The combined findings suggest that 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.

For the purposes of the present dissertation, three implications emerge from the reviewed literature. First, AI acceptance cannot be reduced to technical performance alone, as perceptions are shaped by social and institutional factors. Second, conversational AI lowers barriers to access through natural language interaction, but may also increase the risk of overreliance. Third, healthcare represents a particularly sensitive domain in which trust and perceived risk are likely to become central determinants of acceptance. These insights provide the basis for the following discussion of ChatGPT in health-related contexts.

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.

Overall, ChatGPT occupies an ambivalent position within contemporary health information ecosystems. On the one hand, it may improve access, comprehension, and engagement, particularly in non-urgent and educational contexts. On the other hand, its limitations highlight the need for clear role boundaries, ethical safeguards, and informed user expectations. This duality makes trust and perceived risk central concepts in understanding acceptance of ChatGPT in healthcare.

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).

Taken together, the reviewed literature indicates that trust, perceived risk, and ethical concerns form an interdependent explanatory cluster in AI-based health communication. Trust may facilitate acceptance, but only when users perceive AI-generated information as reliable, transparent, and appropriately bounded. Conversely, perceived risk and ethical uncertainty may weaken acceptance even when the technology is considered useful. For this reason, the present dissertation treats trust and risk as core explanatory dimensions of ChatGPT acceptance.

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 understood as an evaluative orientation toward an object, idea, person, or technology. Attitudes are not limited to rational judgments, but also include emotional reactions and behavioral predispositions. In this sense, attitudes influence how individuals interpret information, evaluate potential benefits and risks, and decide whether to engage with or avoid a given technology (Eagly and Chaiken, 1993).

A widely used perspective conceptualizes attitude as a three-dimensional construct consisting of cognitive, affective, and behavioral components (Rosenberg and Hovland, 1960; Breckler, 1984; Eagly and Chaiken, 1993). The cognitive dimension refers to beliefs and evaluations, such as whether ChatGPT is perceived as useful, reliable, or accurate. The affective dimension captures emotional reactions, including trust, anxiety, discomfort, or enthusiasm. The behavioral dimension reflects action tendencies or intentions, such as willingness to use ChatGPT for health-related information seeking. This tripartite model is particularly relevant in healthcare contexts, where user evaluations often combine rational judgments with emotional responses and behavioral caution.

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. Nevertheless, in healthcare contexts attitudes remain particularly relevant because users often evaluate technologies not only instrumentally, but also emotionally and ethically. (Holden and Karsh, 2010).

Attitudes toward artificial intelligence are shaped by a combination of individual experience, technological familiarity, 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). These considerations are especially relevant in healthcare, where trust, vulnerability, and perceived consequences make attitudes toward AI more complex than in ordinary consumer settings.

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).

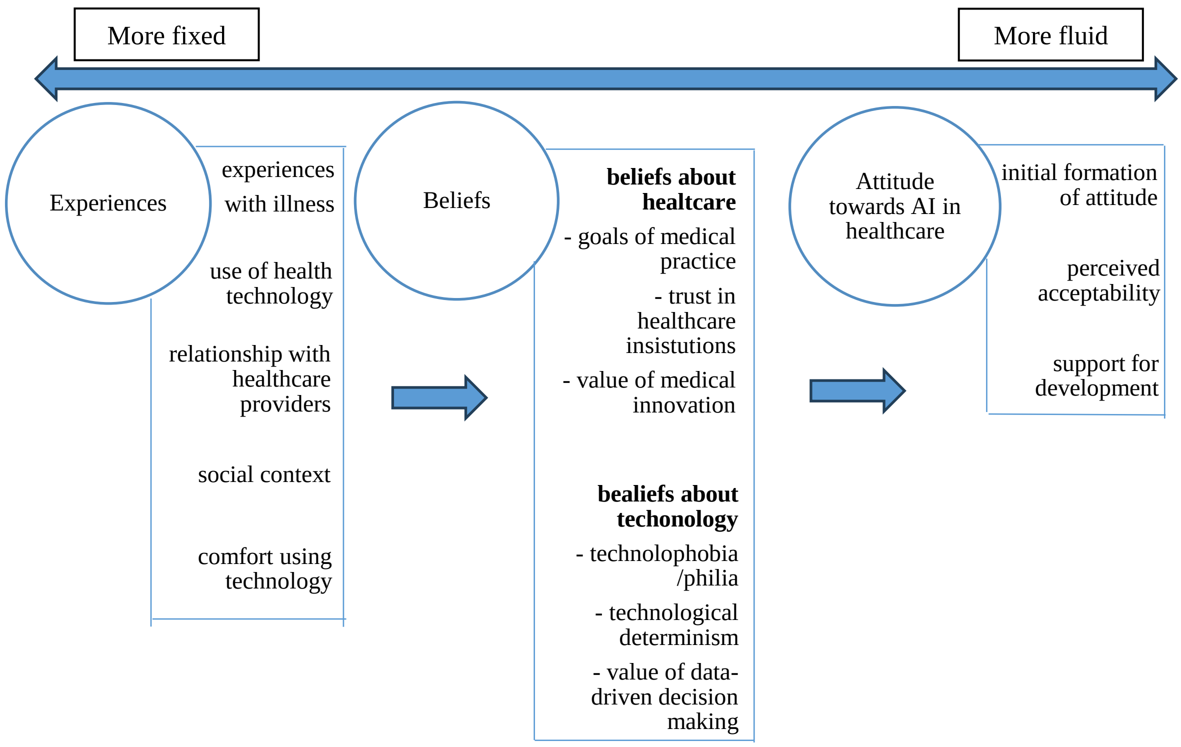
Contextual factors also matter. Attitudes toward ChatGPT may differ depending on whether the system is perceived as a supplementary information source or as a substitute for professional care. Research consistently shows higher acceptance when AI is framed as supporting, rather than replacing, healthcare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

Accordingly, attitudes toward ChatGPT are treated in the present dissertation as an integrative construct that links beliefs about usefulness and trust with willingness to use AI-based health communication tools.

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. . TAM and UTAUT were therefore selected because they remain the most widely applied and empirically validated frameworks for explaining user acceptance of emerging digital systems, including healthcare technologies.

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

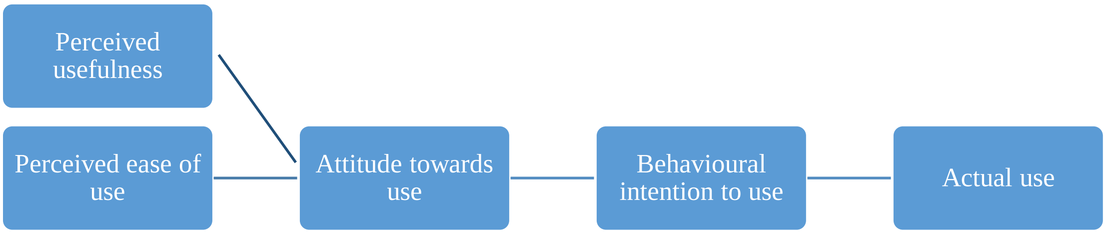
Construct	Definition	Relationship
Perceived Ease of Use (PEOU)	The degree to which a person believes that using a system would be free of effort	Perceived Usefulness
Perceived Usefulness (PU)	The degree to which a person believes that using a system enhances performance	Attitude toward Use
Attitude toward 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 order to clarify the internal logic of the model, Figure 2 presents the original TAM structure. The model assumes that perceived ease of use influences perceived usefulness and attitude toward use, while perceived usefulness directly affects attitude and behavioural intention. Behavioural intention then leads to actual technology use. Thus, TAM is not merely a list of constructs, but a causal acceptance model explaining how instrumental beliefs are translated into intention and use.

Figure 2: Original Technology Acceptance Model



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

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).

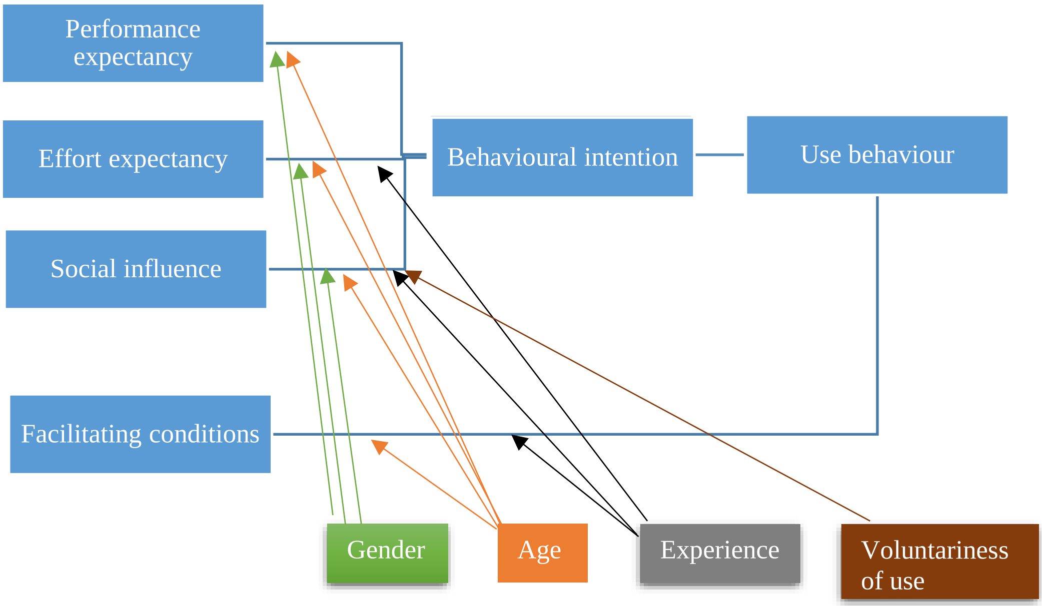
Hungarian TAM-based studies have consistently confirmed the central role of perceived usefulness and perceived ease of use in shaping users' attitudes and behavioral intentions toward digital systems. Research examining the adoption of electronic health services and online health information platforms 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. TAM remains valuable as a parsimonious baseline model, but is insufficient on its own for explaining generative AI acceptance in healthcare.

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 original UTAUT model is presented in Figure 3. Unlike TAM, UTAUT places behavioural intention and use behaviour at the centre of the model and explains them through four core determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. The model also explicitly includes demographic and contextual moderators, such as age, gender, experience, and voluntariness of use.

Figure 3: Original UTAUT model



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

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 adoption by identifying the main determinants that influence users' 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.

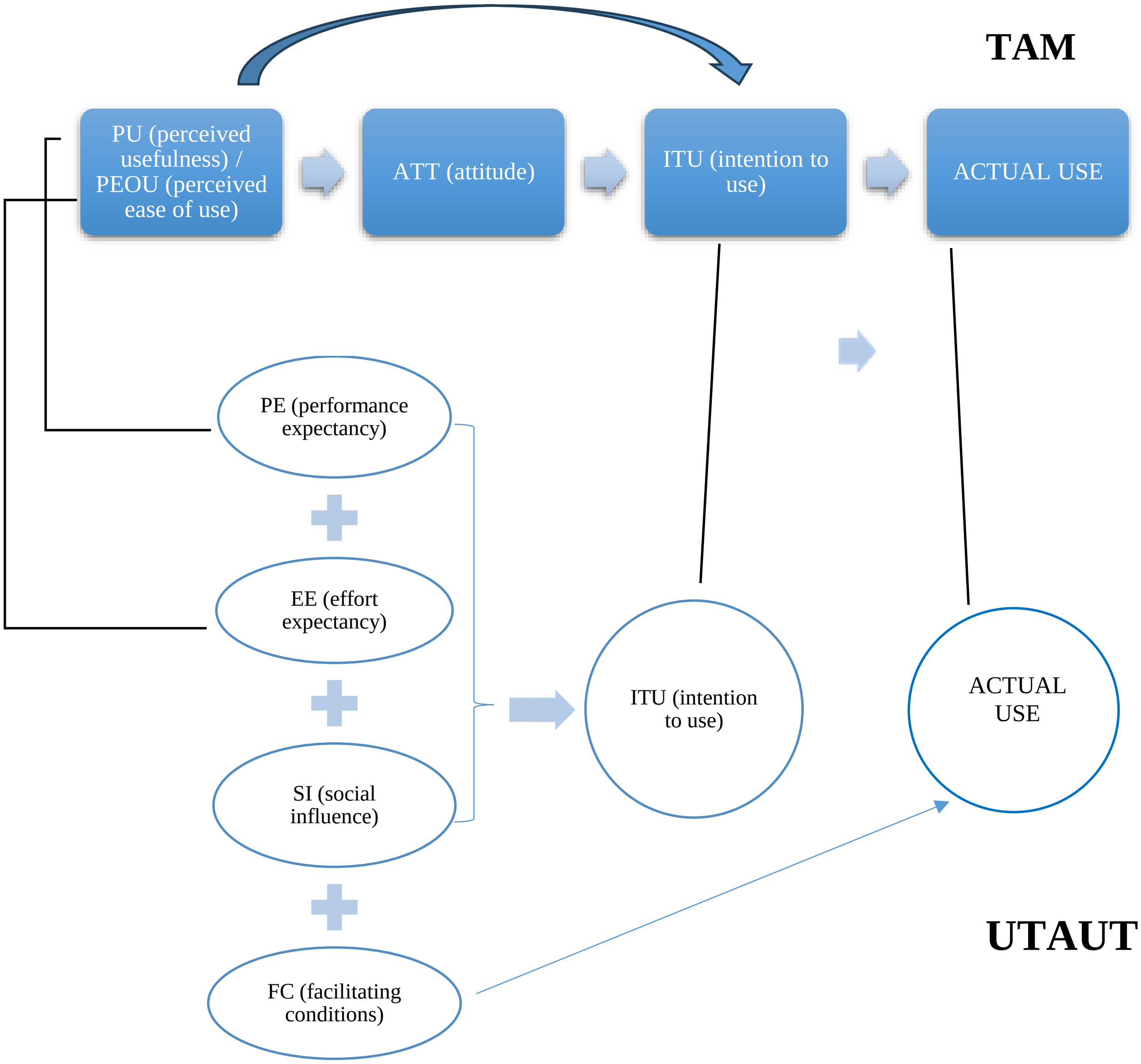
Table 3: Conceptual structure of UTAUT

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)

While TAM and UTAUT share several conceptual foundations, the two models differ substantially in explanatory scope and structural complexity. TAM primarily focuses on individual cognitive evaluations, especially perceived usefulness and perceived ease of use, whereas UTAUT integrates additional social, organisational, and contextual determinants of behavioural intention and use behaviour. Figure 4 illustrates the conceptual relationship between the main constructs of the two frameworks and demonstrates how UTAUT extends the original TAM logic by incorporating social influence, facilitating conditions, and demographic moderators.

Figure 4: Conceptual connection between TAM and UTAUT constructs



Source: Author's own construction based on Davis (1989) and Venkatesh et al. (2003)

As shown in Figure 4, UTAUT can be interpreted as an expanded acceptance framework that retains the core instrumental logic of TAM while introducing broader contextual and moderating dimensions. This broader explanatory structure makes UTAUT particularly relevant for analysing healthcare-related AI acceptance, where trust, social expectations, and contextual conditions play an important role.

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 summarizes the moderating dimensions included in the original UTAUT framework.

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

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)

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.

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).

UTAUT was later extended into UTAUT2, which introduced hedonic motivation, habit, and price value as additional predictors of consumer technology adoption (Venkatesh et al., 2012). While these constructs are relevant in many digital consumption settings, the present dissertation focuses primarily on healthcare-related information seeking, trust, and perceived risk. Therefore, the original UTAUT model provides a more suitable theoretical baseline, while selected insights from later extensions are considered where relevant.

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. In the present dissertation, health-related information seeking is treated as a high-stakes and trust-sensitive context rather than a hedonic consumption setting. Therefore, constructs such as hedonic motivation and price value are of secondary importance compared to trust, perceived usefulness, and perceived risk. 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.

It should be noted that in contemporary AI research, some studies apply a broader interpretation of social influence, extending beyond direct normative pressure to include perceived societal legitimacy, public discourse, and collective expectations. Nevertheless, this differs from the original UTAUT definition and should be interpreted cautiously.

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: Author's 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.

Although the present dissertation focuses on conversational AI rather than physical robots, robot-related attitudes remain theoretically relevant because they capture broader emotional reactions toward autonomous and intelligent non-human systems. Therefore, 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). Negative emotional attitudes toward automation may influence acceptance of AI-supported systems, particularly in contexts where human–machine interaction affects perceived control and psychological comfort (Szatmáry et al., 2023).

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. In this sense, negative attitudes toward robots can be interpreted as a proxy for affective resistance toward intelligent agents more generally, including AI systems such as ChatGPT. ChatGPT is a generative AI conversational system developed by OpenAI and made publicly accessible through a large-scale interactive platform (OpenAI, 2026)

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. This provides the immediate basis for the demographic and integrative synthesis sections that follow.

Based on these considerations, the dissertation adopts a broader acceptance perspective in which trust, perceived risk, eHealth literacy, and role-related expectations are considered alongside traditional technology acceptance constructs.

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).

In the present dissertation, demographic variables are interpreted as theoretically meaningful background characteristics rather than merely descriptive controls. Following UTAUT logic, they may alter the strength and direction of acceptance mechanisms, while also reflecting broader differences in digital socialization, trust formation, and perceived risk.

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). However, observed gender differences should be interpreted probabilistically rather than deterministically.

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	Generally open, but heterogeneous in critical evaluation	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: Author's own collection

This 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).

Taken together, the reviewed evidence suggests that demographic variables should not be treated in isolation. Instead, age, gender, and education are expected to interact with trust, literacy, and perceived usefulness in shaping public acceptance of ChatGPT in healthcare.

3.7 Digital health use and AI-related trust in Hungary and the EU: contextual background

To contextualise the empirical investigation, the dissertation also reviews secondary statistical indicators related to digital health behaviour, digital competence, trust in digital health systems, and attitudes toward AI-supported healthcare in Hungary and the European Union. Although these indicators do not measure attitudes toward ChatGPT directly, they provide important macro-level contextual insights into digital engagement, trust formation, and perceived technological roles (Davis, 1989; Venkatesh et al., 2003; Glikson and Woolley, 2020).

There is a consistent pattern in Hungary: the use of digital health information is widespread, particularly among younger cohorts, while the level of digital competence remains comparatively lower. As shown in Table 8, 73% of the population uses the internet for health-related information, rising to 90% among individuals aged 16–29, while only 63% possess at least basic digital skills. Previous statistical indicators suggest that high digital engagement may coexist with lower levels of trust toward AI-supported healthcare technologies.

Table 8: Digital health information use and digital skills in Hungary and the EU

Indicator	Hungary (%)	EU average (%)	Source
Population with at least basic digital skills	63	54	Eurostat (2023)
Internet use for health-related information (total)	73	75	Eurostat (2023)
Internet use for health information (ages 16–29)	90	88	Eurostat (2023)
Internet use for health information (ages 55+)	53	57	Eurostat (2023)

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

Beyond competence-related differences, secondary data indicate a pronounced imbalance between trust and perceived risk. As presented in Table 9, only 28% of respondents report high trust in digital health services, while 62% express concern about AI-related medical errors. Willingness to rely on digital tools for health decisions remains similarly low. These tendencies are consistent with previous research emphasizing the role of trust and perceived risk in AI acceptance (Glikson and Woolley, 2020; Shin, 2021).

Table 9: Trust and risk perception related to digital health and AI

Indicator	Hungary (%)	EU average (%)	Source
High trust in digital health services	28	41	Eurobarometer (2022)
Willingness to rely on digital tools for health decisions	26	39	Eurobarometer (2022)
Concern about AI-related medical errors	62	58	OECD (2022)

Source: European Commission (2022), Special Eurobarometer 516; OECD (2022), Health at a Glance: Europe – Digital Health Indicators

A further structural pattern concerns the perceived role of AI in healthcare. As shown in Table 10, acceptance of AI as a supportive tool reaches approximately 60%, whereas acceptance of AI replacing medical professionals remains limited to around 22–26%. This distinction suggest that public acceptance of healthcare AI may depend on whether AI is perceived as supportive or substitutive.

Table 10: Acceptance of AI roles in healthcare

Indicator	Hungary (%)	Source
Acceptance of AI as supportive tool	58–64	Eurobarometer (2022); OECD (2022)
Acceptance of AI replacing medical professionals	22–26	Eurobarometer (2022); OECD (2022)

Source: European Commission (2022), Special Eurobarometer 516; OECD (2022), Health at a Glance: Europe

To strengthen analytical comparability, selected indicators were transformed into derived variables. These derived indicators capture the engagement–competence gap, the trust–risk gap, and the support–substitution gap. As shown in Table 11, digital engagement exceeds competence by approximately 10 percentage points, the trust–risk gap reaches –34 points, and acceptance of supportive AI exceeds substitution acceptance by approximately 36 points.

Table 11: Derived indicators based on secondary data

Construct	Indicator Calculation	Hungary (%)	Interpretation
Digital engagement	Health information use (total)	73	High usage
Digital competence	Basic digital skills	63	Moderate level
Engagement–competence gap	73 – 63	+10	Usage exceeds skills
Trust level	High trust in digital health	28	Low trust
Risk perception	Concern about AI errors	62	High concern
Trust–risk gap	28 – 62	–34	Strong imbalance
AI support acceptance	Supportive role	~60	Moderate acceptance
AI substitution acceptance	Replacement role	~24	Low acceptance
Support–substitution gap	~60 – ~24	+36	Strong rejection

Source: Author's own calculations based on Eurostat (2023), Eurobarometer (2022), OECD (2022)

Taken together, the reviewed secondary indicators suggest that digital health engagement, trust formation, and perceptions of AI roles represent important contextual dimensions in healthcare AI acceptance. These broader societal tendencies provide an important background for interpreting the empirical findings presented in the following chapters.

3.8 Summary of theoretical implications

The reviewed literature indicates that public acceptance of ChatGPT in healthcare cannot be sufficiently explained by a single theoretical perspective. Instead, it emerges from the interaction of technological, psychological, social, and contextual factors. Earlier sections of this chapter demonstrated that artificial intelligence should be understood not only as a technical innovation, but also as a socially embedded phenomenon shaped by trust, risk perception, digital competencies, and broader institutional environments (Vial, 2019; Floridi et al., 2018; Rodrigues et al., 2024). This is particularly relevant in healthcare, where decisions are sensitive, uncertainty is often high, and the consequences of misinformation may directly affect individual well-being.

The literature on conversational AI suggests that systems such as ChatGPT occupy a distinctive position within the digital health ecosystem. Unlike traditional health websites or static information portals, ChatGPT enables interactive dialogue, immediate feedback, and personalized explanations through natural language communication. These characteristics may increase perceived usefulness, accessibility, and user engagement in health-realted information seeking contexts. At the same time, the fluent and authoritative communication style of large language models may create misplaced confidence, excessive reliance, or misunderstanding regarding the system's actual capabilities (Howard et al., 2024; Shin, 2021). Consequently, user acceptance depends not only on functionality, but also on how individuals interpret the role, reliability, and limitations of the system.

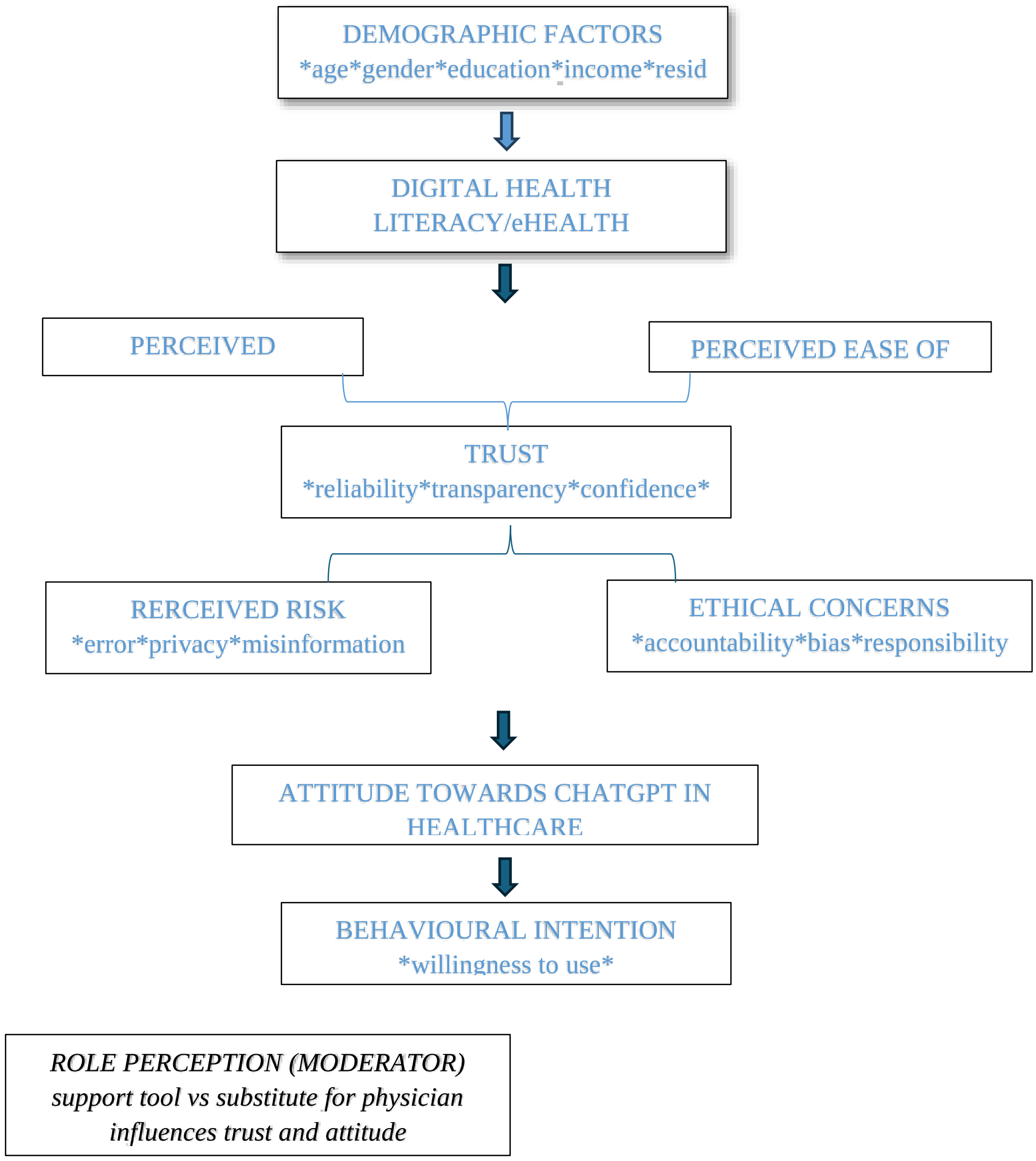
Technology acceptance theories provide an important analytical foundation for understanding these processes. TAM emphasizes the importance of perceived usefulness and perceived ease of use in shaping attitudes and behavioral intention (Davis, 1989). UTAUT broadens this perspective by incorporating performance expectancy, effort expectancy, social influence, facilitating conditions, and demographic moderators such as age and gender (Venkatesh et al., 2003). These models remain highly valuable because they explain why some users perceive ChatGPT as beneficial and easy to use, while others remain reluctant or skeptical. However, the literature also demonstrates that traditional acceptance models alone are insufficient for explaining generative AI adoption in healthcare contexts. In contrast to many ordinary consumer technologies, healthcare-related AI use involves elevated concerns regarding trustworthiness, accountability, privacy, risk, and professional responsibility. Several studies therefore argue that trust should be treated as a central explanatory construct rather than a secondary by-product of usefulness perceptions (Glikson and Woolley, 2020; Kelly et al., 2023). Similarly, perceived risk may weaken acceptance even when users acknowledge the practical advantages of AI systems.

The review further highlighted the importance of user competencies, particularly digital health literacy and eHealth literacy. Individuals differ substantially in their ability to search for, interpret, critically evaluate, and appropriately apply online health information. These competencies are especially relevant in the context of ChatGPT, where responses may appear highly convincing despite possible inaccuracies or oversimplifications. Users with stronger evaluative skills may be better able to calibrate trust and use AI-generated information responsibly, whereas lower literacy levels may increase either avoidance or overreliance (Norman and Skinner, 2006; Diviani et al., 2015).

Demographic factors also appear consistently throughout the literature as meaningful sources of variation in AI acceptance. Age, generational background, gender, education, and digital experience influence perceptions of usefulness, effort, trust, and risk. Younger cohorts often demonstrate greater familiarity and openness toward conversational AI, whereas older groups may place stronger emphasis on reliability, accountability, and human oversight. Educational attainment is similarly associated with stronger digital competencies and more reflective evaluations of AI systems (König and Neumayr, 2022; Chi et al., 2024).

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. Accordingly, the dissertation conceptualizes ChatGPT acceptance as a multidimensional process in which traditional technology acceptance variables are complemented by healthcare-specific trust, perceived risk, literacy-related competencies, demographic characteristics, and role-related expectations. Figure 5 presents the integrated conceptual framework guiding the empirical investigation of the dissertation.

Figure 5: Integrated conceptual framework of ChatGPT acceptance in healthcare



Source: *Author's own construction based on Davis (1989); Venkatesh et al. (2003); Glikson and Woolley (2020); Norman and Skinner (2006); Shin (2021); Rodrigues et al. (2024).*

These theoretical considerations provide the conceptual basis for the empirical investigation presented in the following methodological chapter.

4. HYPOTHESES OF THE DISSERTATION

Building on the literature reviewed in the previous chapters, the acceptance of artificial intelligence in health-related contexts can be understood as the result of a complex interaction between individual characteristics, cognitive evaluations, and contextual influences. Public attitudes toward AI are not determined solely by technical performance or functional efficiency, but are also shaped by trust, perceived risk, prior experience, and the broader social environment in which technology is embedded (Glikson and Woolley, 2020; Rodrigues et al., 2024).

Classical technology acceptance models such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) emphasize that behavioural intention is primarily driven by perceived usefulness, effort expectancy, and social influence. However, recent studies suggest that these models require contextual extension when applied to generative artificial intelligence, particularly in healthcare settings characterized by high uncertainty, accountability concerns, and perceived risk (Shin, 2021; Howard et al., 2024).

In the case of conversational AI systems such as ChatGPT, users evaluate not only whether the technology is useful or easy to use, but also whether it is trustworthy, sufficiently accurate, and appropriate for health-related purposes. Due to its natural language interface and authoritative communication style, ChatGPT introduces evaluation mechanisms that differ from earlier digital health technologies (Tan and Ong, 2024; Pavaloiu and Ioanid, 2024).

Demographic characteristics further shape these evaluations. Previous research demonstrates that age and gender influence technology acceptance, trust formation, and perceived risk. Younger individuals tend to adopt emerging technologies more readily due to greater exposure and familiarity, while gender differences are often associated with variations in perceived technological risk and confidence (Prensky, 2001; Venkatesh et al., 2003; König and Neumayr, 2022; Fritsch et al., 2022).

Trust has been identified as a central determinant of AI acceptance, particularly in high-risk domains such as healthcare. Users are more likely to adopt AI-based tools when they perceive them as reliable, while low levels of trust may hinder behavioural intention regardless of perceived usefulness (Glikson and Woolley, 2020; Shin, 2021). At the same time, research suggests that digital competence does not automatically translate into trust, especially in the case of AI-generated content, where perceived reliability and accountability remain critical concerns (Norman and Skinner, 2006; Neter and Brainin, 2012; Shin, 2021).

Furthermore, acceptance of AI in healthcare appears to be conditional rather than uniform. Users tend to differentiate between supportive and substitutive roles of technology. While AI is often accepted as a complementary tool, it is more likely to be rejected when it replaces human professionals, reflecting concerns related to responsibility and trust (Longoni et al., 2019; Shin, 2021; OECD, 2022).

Based on these theoretical considerations, the dissertation adopts an extended technology acceptance perspective in which demographic characteristics, trust, digital competence, and role-based perceptions jointly shape attitudes toward ChatGPT in healthcare contexts. Accordingly, the following hypotheses are formulated:

Hypothesis 1 (H1): ***Demographic characteristics, particularly age, gender and education, are associated with differences in attitudes and behavioural intention to use ChatGPT in healthcare contexts.*** Demographic variables have long been identified as important moderators in technology acceptance research. The Unified Theory of Acceptance and Use of Technology (UTAUT) explicitly incorporates age, gender, and experience as key factors influencing how individuals perceive and adopt new technologies (Venkatesh et al., 2003). Prior studies consistently show that younger individuals tend to be more open to innovation due to greater digital exposure and familiarity with emerging technologies (Prensky, 2001; König and Neumayr, 2022). At the same time, gender differences have been observed in perceptions of technology, with male users often reporting higher levels of technological confidence and lower perceived risk, while female users tend to exhibit greater sensitivity to uncertainty and trust-related concerns (Venkatesh et al., 2003; Fritsch et al., 2022). Educational attainment also plays a role, as higher levels of education are generally associated with greater digital competence and more differentiated evaluation of information sources (Neter and Brainin, 2012; Chi et al., 2024). These findings therefore suggest that demographic background shapes how individuals evaluate and engage with AI-based health tools, including ChatGPT.

Hypothesis 2 (H2): ***Digital health literacy is not a strong predictor of trust in ChatGPT, indicating a gap between competence and trust in digital health contexts.*** Digital health literacy reflects individuals' perceived ability to search for, understand, and apply online health information (Norman and Skinner, 2006). Higher levels of digital competence are typically associated with increased confidence in using digital tools (Neter and Brainin, 2012). However, recent research suggests that competence does not automatically translate into trust, particularly in the context of artificial intelligence and AI-generated content (Shin, 2021).

Users may feel capable of navigating digital environments while remaining skeptical toward the reliability, accuracy, and accountability of AI-based systems. This distinction reflects a structural gap between competence and trust, which becomes especially relevant in healthcare contexts where perceived risk is high. Therefore, higher levels of digital health literacy are not necessarily associated with higher trust in ChatGPT.

Hypothesis 3 (H3): ***More positive trust-related attitudes toward healthcare AI are associated with more positive attitudes and behavioural intention toward ChatGPT use in healthcare contexts.*** Trust is widely recognized as a central determinant of AI acceptance, particularly in high-risk domains such as healthcare (Glikson and Woolley, 2020). While TAM emphasizes perceived usefulness as a primary driver of behavioural intention (Davis, 1989), more recent studies highlight that trust plays a complementary role by shaping how users evaluate the reliability and credibility of technology (Shin, 2021; Rodrigues et al., 2024).

Users are more likely to perceive AI systems as useful and to adopt them when they consider them trustworthy. Conversely, low levels of trust may significantly reduce behavioural intention, even when the technology offers clear functional benefits. This suggests that trust acts as a key mechanism linking cognitive evaluation and behavioural intention.

Hypothesis 4 (H4): ***Acceptance of ChatGPT in healthcare is conditional: users are more willing to accept it as a supportive tool than as a substitute for medical professionals.*** Previous research indicates that acceptance of artificial intelligence in healthcare is strongly dependent on the perceived role of the technology (Longoni et al., 2019; Shin, 2021). While users tend to accept AI as a complementary tool that supports information seeking or decision-making, they are more likely to reject scenarios in which AI replaces human professionals. This distinction reflects concerns related to responsibility, accountability, and trust in high-stakes environments such as healthcare. As a result, acceptance is not uniform but structured around clearly defined role boundaries, with higher acceptance for supportive functions and lower acceptance for substitutive roles (Longoni et al., 2019; Shin, 2021,; OECD, 2022)

Hypothesis 5 (H5): ***Traditional UTAUT predictors are insufficient to fully explain acceptance of AI in healthcare, as trust and role-based perceptions play an additional role.*** Although UTAUT provides a robust framework for explaining technology adoption (Venkatesh et al., 2003), its explanatory power may be limited in contexts characterized by high uncertainty and risk. In the case of generative AI, users must evaluate not only usefulness and ease of use, but also trustworthiness, reliability, and appropriateness for specific roles (Glikson and Woolley, 2020; Shin, 2021). Recent literature highlights the need to extend traditional models by incorporating trust and context-specific factors, particularly in healthcare environments

(OECD, 2022; Rodrigues et al., 2024). Role-based perceptions—whether AI is viewed as supportive or substitutive—represent an additional dimension that influences acceptance beyond classical predictors. Therefore, behavioural intention cannot be fully explained by traditional UTAUT constructs alone.

These hypotheses provide a structured analytical framework linking the theoretical background to the empirical investigation. They allow the systematic examination of how demographic characteristics, trust, and role-based perceptions influence the acceptance of generative AI in healthcare-related contexts. The hypotheses are tested using a multi-source empirical design combining a university-based sample, a representative population survey, and secondary statistical indicators. This triangulated approach enables the identification of both structural patterns and subgroup-specific differences, thereby strengthening the robustness and interpretability of the findings.

5. METHODOLOGY

This chapter outlines the methodological approach applied in the dissertation. The structure follows a multi-source research design to enable methodological triangulation across different levels of analysis and strengthens the robustness of the findings.

5.1 Research design and process

The dissertation applies a multi-source research design in order to examine public acceptance of ChatGPT in health-related contexts from several complementary perspectives. The research design integrates secondary statistical data, a primary survey among university students, and a complementary representative survey among adults aged 40 years and above. This structure was chosen because no single dataset would be sufficient to capture both broader population-level tendencies and individual-level attitudes toward generative AI in healthcare.

The secondary statistical data provide the macro-level context of the research by identifying broader structural patterns in digital health information use, digital competence, trust in digital health services, and attitudes toward AI-supported healthcare. The primary survey provides detailed micro-level evidence on attitudes toward ChatGPT among younger and digitally active respondents. The complementary representative 40+ survey extends the analysis by focusing on older age groups and supports the interpretation of generational and demographic differences.

The logic of the research therefore follows a structured analytical progression. First, secondary data establish the broader social and digital health context in which ChatGPT acceptance can be interpreted. Second, the primary empirical dataset allows the detailed examination of trust, perceived usefulness, digital health literacy, and behavioural intention. Third, the representative 40+ dataset provides an additional validation layer, particularly for assessing whether age- and generation-related patterns are consistent across older population groups. This multi-source approach enables methodological triangulation by combining macro-level indicators, micro-level survey data, and representative population evidence. This is particularly important because acceptance of AI in healthcare is shaped not only by individual attitudes, but also by digital competence, trust, perceived risk, role perception, and demographic background (Venkatesh et al., 2003; Glikson and Woolley, 2020; Shin, 2021).

Figure 6 summarizes the logical progression of the research design, moving from secondary contextual analysis to primary empirical investigation and complementary validation.

Figure 6: Logical progression of research design

Source: Author's own work

This triangulated design is particularly relevant in the context of AI acceptance research, where attitudes may vary significantly across population groups and contexts. By combining macro-level statistical indicators, a student-based exploratory dataset, and a representative 40+ sample, the study reduces the risk of sample-specific bias and increases the robustness and interpretability of the findings (OECD, 2024).

5.2 Secondary data collection and analytical use

In addition to the primary survey data, secondary statistical datasets were reviewed to provide contextual background for the empirical analysis. Secondary indicators were collected from Eurostat, Eurobarometer, OECD, and Hungarian Central Statistical Office (KSH) databases. The analysis focused on indicators related to digital health information use, digital competence, trust in digital health services, perceived AI-related risks, and attitudes toward AI-supported healthcare.

These secondary indicators were not used for direct hypothesis testing, but rather for contextual interpretation and triangulation of the primary empirical findings. The secondary analysis therefore served a complementary and interpretive function within the overall research design.

5.3 Empirical data collection and measurement

The primary empirical study was designed to examine attitudes toward ChatGPT in healthcare among younger, digitally active respondents, with particular focus on trust, perceived usefulness, digital health literacy, and behavioural intention. This dataset provides the main basis for testing H2, H3, and H5, while also contributing to H1 and H4.

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. A total of 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 captured trust in AI-based health communication, perceived usefulness, behavioural intention, health information-seeking behaviour, expectations regarding the role of ChatGPT in healthcare, and 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 (Davis, 1989; Venkatesh et al., 2003).

The eHEALS scale measured digital health literacy, while the NARS scale captured negative attitudes toward robots and AI. These instruments made it possible to distinguish between digital competence, emotional resistance, and trust in AI-generated health information. This distinction is particularly relevant for H2, which assumes a gap between competence and trust (Norman and Skinner, 2006; Neter and Brainin, 2012; Shin, 2021).

Two additional item blocks were included: an 8-item scale on AI/robot attitudes in healthcare and a 5-item ChatGPT-specific module. The ChatGPT-specific items measured perceived reliability, societal usefulness, behavioural substitution, use for sensitive topics, and expected future integration into healthcare. These items are especially relevant for H3, H4, and H5. In the self-developed items, UTAUT constructs were used as conceptual reference points rather than as fully validated latent constructs. In particular, items mapped to social influence should be interpreted as indicators of perceived social and societal role of AI rather than as direct measures of normative pressure in the original UTAUT sense.

The internal consistency of multi-item scales was assessed using Cronbach's alpha. The ChatGPT-specific scale demonstrated acceptable reliability ($\alpha = 0.79$), while the AI/robot attitude scale showed lower internal consistency ($\alpha = 0.43$), indicating a multidimensional construct. Therefore, the AI/robot scale was retained for exploratory interpretation rather than treated as a strictly unidimensional measure.

The primary sample was strongly skewed toward younger respondents, with 90.7% belonging to Generation Z. The gender distribution was relatively balanced, and educational attainment was comparatively high, reflecting the study's focus on digitally active and education-oriented respondents. Although the sample is not representative of the Hungarian population, it provides analytically valuable insight into early-stage users of conversational AI technologies.

The demographic composition of the student sample reflects a digitally experienced population, making it particularly suitable for examining early-stage adoption patterns and attitudes toward generative AI. This is especially relevant for interpreting H1 and H2, as well as the relationship between digital competence and trust.

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 12).

Table 12: 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.g. childcare responsibilities*
Source: Author's own data collection

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 H1, which assumes generational differences in AI acceptance and trust.

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, particularly in the context of demographic differences (H1) and the relationship between competence and trust (H2).

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 whether higher levels of digital health literacy are associated with higher trust in ChatGPT, as proposed in H2.

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 (H1) and the broader interpretation that acceptance of AI may be influenced by factors beyond traditional utility-based models (H5).

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 13: 8-item self-developed questionnaire on attitudes toward robots and Artificial Intelligence in medical contexts

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 medical professionals 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's 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 provide the empirical basis for examining trust, perceived usefulness, behavioural intention, and the distinction between supportive and substitute uses of ChatGPT, which is directly relevant to H3 and H4 (Table 13).

Table 14: 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 medical professional.	Facilitating Conditions (FC)	Suggests that ChatGPT's 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 medical professional 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's 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.

To complement the primary survey, an additional empirical dataset was included to examine attitudes toward ChatGPT among adults aged 40 and above. This dataset primarily supports the examination of H1 and H4 by enabling the interpretation of generational differences and role-based acceptance patterns. 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. At the time of survey design and data collection, the detailed, publicly accessible microdata from the 2022 census were not yet fully available in a format suitable for quota-based sampling. Therefore, the 2011 census remained the most stable and methodologically consistent benchmark. 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.

The 40+ survey used the same five ChatGPT-related items as the primary survey, but responses were recorded on a four-point forced-choice scale. This design was intended to elicit clear directional attitudes and to avoid neutral midpoint responses. Although the two empirical datasets are not directly comparable due to differences in sampling and scale format, they provide complementary evidence regarding trust, role perception, and generational differences. In the 40+ dataset, responses were measured on a four-point forced-choice scale, where 1 indicated the strongest agreement and 4 indicated the strongest disagreement. Consequently, lower mean values indicate higher acceptance or stronger agreement. The demographic structure of the 40+ sample allows for a more reliable interpretation of age-related differences in AI acceptance, particularly in relation to H1. The relatively balanced gender distribution and varied educational background also provide a suitable basis for examining demographic influences on attitudes toward ChatGPT in healthcare contexts.

Table 15: 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 11).

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.

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 from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

The eHEALS scale was used to assess respondents' perceived ability to find, evaluate, and apply online health information (Norman and Skinner, 2006). Scores range from 8 to 40, with higher values indicating higher perceived digital health literacy. This allows the analysis to distinguish between competence and trust, which is directly relevant to H2.

The NARS scale captures emotional, cognitive, and social resistance toward AI-based systems (Shin, 2021). This makes it possible to identify underlying discomfort or skepticism that may influence acceptance beyond perceived usefulness, supporting the interpretation of H1 and H5.

5.4 Comparison of the two empirical datasets

The key methodological differences between the two empirical datasets are summarized in Table 16. The comparison highlights differences in sampling strategy, target population, response scale, and analytical role.

Table 16: 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

The two datasets are complementary rather than directly comparable. The primary dataset provides detailed attitudinal insights among younger, digitally active respondents, while the representative 40+ dataset offers population-level validation for older age groups. Together with the secondary data, these empirical components enable triangulation across macro-level indicators, student-based micro-level attitudes, and representative population evidence.

5.5 Data analysis and hypothesis testing strategy

Data analysis combined descriptive statistics, reliability analysis, ANOVA, and linear regression. Descriptive statistics were used to summarize the main characteristics of the samples and the central tendencies of the examined variables. Reliability analysis was conducted using Cronbach's alpha to assess the internal consistency of multi-item scales.

ANOVA was applied to examine group differences across demographic variables, including age, gender, education, residence, and income. These analyses were used primarily to test H1, which examines whether demographic characteristics are associated with differences in attitudes and behavioural intention to use ChatGPT.

Prior to inferential analysis, statistical assumptions were examined. Normality was assessed using skewness and kurtosis indicators, while homogeneity of variance was evaluated using Levene's test. Statistical significance was evaluated at the $p < 0.05$ level.

H2 was examined by analysing the relationship between digital health literacy and trust in ChatGPT, primarily through regression-based and comparative interpretation. Linear regression analysis was used to examine relationships between trust, perceived usefulness, and behavioural intention, corresponding primarily to H3. The coefficient of determination (R^2) was used to assess explanatory power. Although structural equation modelling is frequently used in UTAUT-based studies, regression analysis was selected due to sample size limitations and the exploratory nature of the model extension (Venkatesh et al., 2003; Venkatesh et al., 2016).

H4 was examined through item-level and cross-dataset comparison of supportive versus substitutive AI roles. This hypothesis was tested by comparing acceptance of ChatGPT as a supportive information tool with willingness to use it as a substitute for medical professionals. H5 was examined through the combined interpretation of regression results, secondary indicators, and role-based findings. This hypothesis assesses whether traditional UTAUT predictors are sufficient in the context of AI-based healthcare, or whether trust and role-based perceptions provide additional explanatory value.

Analyses were conducted using Microsoft Excel and SPSS 16.0. Each statistical method was selected to correspond directly to the research objectives and hypotheses. Descriptive statistics provided the empirical overview, ANOVA tested demographic differences, reliability analysis assessed the consistency of the applied scales, and regression analysis examined the relationships among trust, usefulness, and behavioural intention.

Taken together, the analytical strategy ensures a clear connection between the theoretical framework, empirical data, and tested hypotheses. Although the primary sample does not allow statistical generalization to the Hungarian population, the combined use of secondary data, an university-based survey, and a representative 40+ dataset supports a nuanced interpretation of acceptance patterns toward ChatGPT in healthcare.

Although structural equation modeling (SEM) is frequently applied in UTAUT-based studies, the present research applies regression analysis due to both sample size considerations and the exploratory nature of the model extension. In addition, the inclusion of trust and role-based perceptions as emerging constructs supports a stepwise analytical approach rather than a fully specified structural model (Venkatesh et al., 2003; Shin, 2021).

Each hypothesis is linked to a specific analytical strategy. H1 is examined through ANOVA-based group comparisons across demographic variables. H2 and H3 are tested using regression analysis, focusing on the relationship between digital health literacy, trust, perceived usefulness, and behavioural intention. H4 is analysed through comparative evaluation of role-based acceptance across datasets, while H5 is assessed through the combined interpretation of regression results and secondary data patterns. This structured approach ensures a direct alignment between theoretical assumptions and empirical testing.

5.6 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 based on three complementary sources: the primary student survey, the representative 40+ dataset, and secondary statistical indicators related to digital health behaviour and AI acceptance.

6.1 Descriptive statistics of the main constructs and the competence-trust gap

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 17).

Table 17: 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	3.86
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, indicating relatively high perceived competence in searching for, evaluating, and using online health information. Given the university student composition of the sample, this result is consistent with previous research on digitally active populations (Prensky, 2001; Norman and Skinner, 2006).

Negative attitudes toward robots (NARS) yielded a mean score of 42.18 (SD = 7.07) on a 14–70 scale, indicating moderate reservation toward automation and robotics. The relatively high standard deviation suggests substantial internal variation within the sample, with respondents differing considerably in their openness toward AI-based systems. This pattern is consistent with previous studies highlighting heterogeneous attitudes toward AI even among digitally experienced populations (Shin, 2021; Fritsch et al., 2022).

The 8-item healthcare-focused AI attitude scale produced a mean score of 25.19 (SD = 3.86), indicating a generally moderate orientation toward AI and robotics in healthcare. Because the scale includes both positively and negatively framed items, the result reflects ambivalent attitudes combining openness toward innovation with concerns regarding trust, autonomy, and medical responsibility. Similar patterns have been identified in previous healthcare AI studies (Longoni et al., 2019; Glikson and Woolley, 2020).

The ChatGPT-related scale showed a mean of 12.77 (SD = 3.94) on a 5–25 scale, indicating cautious rather than strongly positive attitudes toward conversational AI in healthcare. Compared to the other constructs, this scale also displayed substantially greater variability, suggesting that evaluations of ChatGPT are less stable and more uncertainty-driven than broader AI attitudes or digital health competence.

To better understand variability across constructs, relative dispersion was also calculated using the coefficient of variation (CV) (Table 18).

Table 18: 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	3.86	12.9
ChatGPT	12.77	3.94	30.9

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

The results reveal clear differences in response consistency across the examined constructs. The healthcare-focused AI scale showed the lowest relative variability (CV = 12.9%), followed by NARS (CV = 16.8%) and eHEALS (CV = 19.0%), indicating relatively stable and homogeneous evaluations within the sample. In contrast, the ChatGPT-related scale demonstrated substantially higher variability (CV = 30.9%), suggesting more divided and less consolidated attitudes toward conversational AI in healthcare contexts. While some respondents appeared relatively open to ChatGPT-related health use, others remained clearly skeptical. Compared to broader AI-related constructs, ChatGPT evaluations therefore appear more uncertainty-driven and situational (Shin, 2021; Rodrigues et al., 2024). This higher variability supports the decision to examine ChatGPT attitudes not only at the composite level but also through item-level analysis in later sections.

From an analytical perspective, this finding supports the decision to examine ChatGPT attitudes not only through aggregate scores but also at the item level in later sections. Composite indicators alone may obscure important differences in how respondents evaluate specific aspects of conversational AI in healthcare.

Comparison with theoretical scale midpoints further highlights the competence–trust distinction. While eHEALS scores were clearly above the midpoint, ChatGPT attitudes remained below it, indicating greater skepticism toward conversational AI in healthcare contexts. This competence–trust gap becomes even more visible when standardized values are compared. Digital health literacy reached approximately 72% of its theoretical maximum, whereas the ChatGPT scale reached only 51%, producing a difference of more than 20 percentage points. The magnitude of this gap provides initial support for Hypothesis 2, suggesting that digital health literacy alone is not a strong predictor of trust in ChatGPT. The findings also indicate that trust, perceived risk, and role-based interpretation represent additional explanatory dimensions beyond traditional technology acceptance variables.

Group comparisons and regression analyses were preceded by assumption testing. Shapiro–Wilk tests indicated statistically significant deviations from normality for all main composite variables: eHEALS ($p = 0.007$), NARS ($p < 0.001$), the AI/robot attitude scale ($p < 0.001$), and the ChatGPT-related scale ($p = 0.001$). However, skewness and kurtosis values remained within acceptable ranges: eHEALS (skewness = -0.341; kurtosis = 0.887), NARS (skewness = 0.814; kurtosis = 1.902), AI/robot scale (skewness = 0.693; kurtosis = 1.983), and ChatGPT scale (skewness = 0.598; kurtosis = 0.633). Given the sample size ($N = 172$), the applied parametric procedures were therefore considered sufficiently robust for interpretation.

Homogeneity of variance was assessed using Levene's tests. In most group comparisons, the assumption of equal variances was satisfied. The main exception concerned the income-based comparison for NARS scores, where the Levene test was significant; therefore, income-related NARS findings are interpreted cautiously and primarily as exploratory.

Internal consistency analyses showed acceptable to high reliability for most scales. The eHEALS scale demonstrated excellent reliability (Cronbach's $\alpha = 0.881$), while the NARS scale ($\alpha = 0.717$) and the ChatGPT-related scale ($\alpha = 0.787$) showed acceptable internal consistency. In contrast, the healthcare-focused 8-item AI scale showed low reliability ($\alpha = 0.432$), indicating that this construct captures a heterogeneous and multidimensional attitudinal domain. Consequently, this scale was retained for exploratory interpretation rather than treated as a strictly unidimensional measure.

6.2 Sociodemographic differences in digital health literacy and AI attitudes

The relationship between sociodemographic background and attitudes toward AI-based healthcare technologies was examined across gender, age, education, place of residence, and income categories. These analyses primarily address Hypothesis 1, which assumes that demographic characteristics are associated with differences in attitudes and behavioural intention toward ChatGPT use in healthcare contexts.

Previous research identifies demographic variables as important moderators of technology-related perceptions and behaviour, particularly in healthcare AI contexts where competence, trust, and perceived risk interact simultaneously (Venkatesh et al., 2003; Glikson and Woolley, 2020; Shin, 2021).

Overall, demographic effects proved selective rather than uniform across constructs. Education was more strongly associated with digital health literacy and emotional attitudes toward automation, whereas ChatGPT-related attitudes were more closely linked to gender-related differences in trust and risk perception.

6.2.1 Digital health literacy across sociodemographic groups

Table 19 summarizes the distribution of eHEALS scores across the main sociodemographic categories.

Table 19: 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

Overall, only modest differences emerge across most groups. Women reported slightly higher eHEALS scores than men (29.08 vs. 28.18), although this difference did not reach statistical significance. Similarly, older respondents within the sample (29–44 years) reported somewhat higher digital health literacy than younger participants, but the difference remained descriptive rather than statistically significant.

More pronounced differences emerged 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; $p = 0.012$). A similar pattern emerged for ongoing studies: respondents enrolled in MA/MSc or higher programmes reported higher digital health literacy than BA/BSc or lower students (31.24 vs. 28.33; p = 0.020). These findings are consistent with previous studies suggesting that educational attainment strengthens both actual and perceived competence in evaluating online health information (Norman and Skinner, 2006; Neter and Brainin, 2012).

Higher digital competence, however, did not necessarily correspond to stronger trust in AI-based healthcare tools, a distinction examined further in later analyses.

Income and place of residence showed no significant effects, suggesting that digital health literacy within this relatively homogeneous student sample was influenced primarily by educational factors. Table 20 provides a more detailed overview of statistical significance across the examied demographic variables.

Table 20: 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	0.012	*
Ongoing studies	t-test	0.020	*

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

The results indicate that education was the only consistent predictor of digital health literacy, while gender, age, residence, and income remained non-significant. A more detailed picture emerges when examining the individual eHEALS items (Table 21).

Table 21: 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).

The item-level results indicate that respondents felt particularly confident in locating and accessing online health information, while lower scores appeared for critical evaluation and decision-making confidence. This suggests that respondents perceived themselves as capable of finding health information online but less certain about evaluating reliability and applying information critically. This distinction is particularly relevant for conversational AI systems such as ChatGPT, where responses may appear authoritative despite potential inaccuracies (Shin, 2021). Accordingly, high digital health literacy should not automatically be interpreted as equivalent to trust in AI-generated health information.

6.2.2 Emotional attitudes toward robots and healthcare AI

Attitudes toward AI in healthcare are shaped not only by competence-related factors but also by emotional responses toward automation. These dimensions were captured through the NARS scale and the 8-item healthcare-focused AI attitude scale (Table 22).

Table 22: 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, indicating the presence of emotional reservation toward automation. Group comparisons revealed significant differences by educational background: completed education ($p = 0.005$) and ongoing level of studies ($p = 0.006$) were both significantly associated with NARS scores.

Table 23 summarizes the statistical significance of group differences for both NARS and the healthcare-focused AI scale.

Table 23: 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	0.082	0.038	Gender effect only for AI scale
Age	0.072	0.313	Not significant
Residence	0.501	0.085	Not significant
Relative income	0.451	0.051	Weak/borderline effect
Highest completed education	0.005	0.262	Strong effect on NARS only
Ongoing studies	0.006	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).

The results reveal a distinction between general emotional attitudes toward robots and healthcare-specific AI evaluations. Education showed a significant relationship with NARS, indicating lower emotional resistance toward automation among respondents with higher educational attainment. However, this effect did not extend to the healthcare-focused AI scale.

In contrast, gender differences appeared primarily in the healthcare-focused AI scale rather than in NARS. Male respondents reported more positive attitudes toward healthcare AI applications, while gender differences in general emotional attitudes toward robots remained non-significant.

These findings suggest that different sociodemographic variables influence general technological attitudes and context-specific healthcare AI evaluations in different ways.

6.2.3 Variability in ChatGPT-related attitudes

Additional differences emerge when examining the distribution of ChatGPT-related attitudes across demographic groups (Table 24).

Table 24: 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

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

The results indicate that male respondents reported both higher mean scores and slightly greater consistency in their evaluations of ChatGPT. Female respondents showed lower overall acceptance, while younger respondents displayed somewhat greater variability, suggesting less consolidated attitudes toward conversational AI.

Importantly, education does not significantly influence ChatGPT-related attitudes, despite its strong relationship with digital health literacy and emotional attitudes toward robots. This finding is particularly relevant for Hypothesis 2, as it suggests that trust in ChatGPT is not primarily determined by competence-related factors.

Overall, the findings provide partial support for Hypothesis 1. Demographic effects were selective rather than universal: education primarily shaped competence and emotional openness toward automation, whereas gender was more strongly associated with trust-related evaluations of conversational AI. Age-related effects remained limited within the relatively homogeneous student sample and are examined further in the representative 40+ dataset.

6.3 General attitudes toward AI and emotional responses to automation

Attitudes toward AI in healthcare are shaped not only by perceived usefulness and digital competence, but also by emotional responses toward automation and technological uncertainty (Glikson and Woolley, 2020; Shin, 2021).

The NARS scale and the 8-item healthcare-focused AI attitude scale provide insight into these emotional dimensions. Overall, respondents did not display strong rejection toward AI and robotics, but moderate emotional reservation and caution were evident.

As shown in Tables 23–25, higher educational attainment was associated with lower emotional resistance toward robots, suggesting that familiarity and competence may reduce generalized technological anxiety. However, this effect became weaker when respondents evaluated concrete healthcare-related AI applications.

Respondents appeared more accepting of general technological support and automation than of healthcare situations involving responsibility, trust, and medical decision-making. This finding suggests that attitudes toward AI are multidimensional and context-dependent. While respondents generally supported assistive and efficiency-enhancing functions, they remained more cautious toward autonomous or substitutive AI roles (Longoni et al., 2019; Glikson and Woolley, 2020).

The findings further indicate that high digital health literacy does not eliminate emotional caution toward AI systems. Together, these results provide partial support for Hypothesis 1 and preliminary support for Hypothesis 4 and Hypothesis 5 by suggesting that AI acceptance depends strongly on trust and perceived technological role.

6.4 Perceptions of ChatGPT in healthcare

Among the examined constructs, attitudes toward ChatGPT proved to be the most differentiated. While respondents reported relatively high digital health literacy and moderate openness toward AI in healthcare, evaluations of conversational AI remained substantially more cautious and context-dependent.

The overall ChatGPT-related scale mean (12.77 out of 25) indicates cautious openness rather than strong acceptance. Compared with the other constructs, ChatGPT-related attitudes also showed higher variability, suggesting greater uncertainty and less consolidated evaluations.

Gender was the only sociodemographic variable showing a strong and statistically significant relationship with ChatGPT-related attitudes ($p = 0.0006$). Male respondents reported higher levels of trust and openness toward ChatGPT than female respondents. In contrast, education did not significantly influence ChatGPT-related attitudes despite its strong association with digital health literacy and emotional openness toward automation. This finding supports the interpretation that competence and trust represent partially separate evaluative dimensions. A more detailed pattern emerges from the item-level analysis (Table 25).

Table 25: 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 medical professional.	1.80	0.90
4. I would rather go to ChatGPT with uncomfortable, overly personal questions than see a medical professional 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

The findings reveal a structured rather than uniform pattern of acceptance. Trust in ChatGPT as a source of medical information remained relatively limited, indicating hesitation toward relying on conversational AI in personal healthcare situations.

At the same time, respondents evaluated the broader societal usefulness of ChatGPT more positively, particularly regarding access to information and health literacy. In contrast, the strongest rejection appeared in relation to replacing medical professionals. Respondents clearly rejected the idea of turning to ChatGPT more often than to healthcare professionals, indicating a clear boundary between supportive AI use and professional medical care.

Attitudes toward using ChatGPT for sensitive or embarrassing questions were more mixed, suggesting a tension between convenience and trust. Despite current caution, many respondents nevertheless believed that ChatGPT would become part of everyday healthcare in the future.

Overall, attitudes toward ChatGPT appear structured around clear trust and role boundaries. Respondents were substantially more willing to accept conversational AI in supportive and informational functions than in substitutive medical roles. Table 26 summarizes the statistical significance of group differences in ChatGPT attitudes.

Table 26: Statistical significance of group differences in ChatGPT attitudes (N=172)

Grouping variable	p-value	Interpretation
Gender	0.0006	***
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).

Taken together, the findings support Hypothesis 4 and further suggest that traditional UTAUT-related predictors alone are insufficient to explain conversational AI acceptance in healthcare. Trust, perceived risk, and role-based interpretation emerge as additional explanatory dimensions.

6.5 Sociodemographic patterns in AI and ChatGPT attitudes

While the previous sections examined individual constructs separately, this section summarizes the broader sociodemographic patterns emerging across the dataset. The findings indicate that demographic variables influence different dimensions of AI acceptance selectively rather than uniformly (Table 27).

Table 27: 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

Education emerged as the most consistent factor shaping digital competence and general emotional attitudes toward AI. Higher educational attainment was associated with stronger digital health literacy and lower emotional resistance toward automation. However, education did not significantly influence ChatGPT-related trust or acceptance.

Gender showed a different pattern. While gender differences remained relatively limited for digital health literacy and general AI attitudes, they became substantially stronger in relation to ChatGPT-related perceptions. Male respondents consistently reported higher levels of openness and trust toward conversational AI applications than female respondents.

Age-related effects remained relatively weak within the student sample due to its homogeneous composition. Place of residence and income also showed only limited and inconsistent effects across the examined constructs.

Overall, the findings suggest that education primarily shapes competence-related dimensions, whereas gender appears more strongly associated with trust-related evaluations of conversational AI. This distinction supports the interpretation that competence and trust operate as partially separate dimensions in AI acceptance.

From the perspective of the hypotheses, the results provide partial support for Hypothesis 1 and further reinforce Hypothesis 2 by indicating that higher digital competence does not necessarily translate into greater trust toward conversational AI systems.

6.6 Interrelationships between digital competence, AI attitudes, and ChatGPT perceptions

To examine the relationships between the main constructs, a series of linear regression analyses were conducted between digital health literacy (eHEALS), negative attitudes toward robots (NARS), the healthcare-focused AI attitude scale, and the ChatGPT-related scale. These analyses primarily contribute to the interpretation of Hypothesis 2, Hypothesis 3, and Hypothesis 5. Table 28 summarizes the regression results.

Table 28. Linear regression analyses (scale totals, N=172)

Variables	R²	P-value
eHEALS vs NARS	0.00003	p=0.940
8-item (AI attitude) scale vs eHEALS	0.0528	p=0.002
8-item (AI attitude) scale vs NARS	0.0119	p=0.154
5-item (ChatGPT) scale vs eHEALS	0.0676	p<0.001
5-item (ChatGPT) scale vs NARS	0.0220	p=0.052
5-item (ChatGPT) scale vs 8-item (AI attitude) scale	0.3008	p<0.001

Source: Author's own calculation

Overall, the models revealed relatively weak relationships between most constructs. Digital health literacy explained virtually none of the variance in negative attitudes toward robots ($R^2 \approx 0.000$), and only a small proportion of variance in both the healthcare-focused AI scale and the ChatGPT-related scale.

Similarly, associations involving NARS were weak. Emotional resistance toward robots explained only a very limited proportion of variance in both healthcare-related AI attitudes and ChatGPT perceptions.

The strongest relationship emerged between the healthcare-focused AI attitude scale and the ChatGPT-related scale ($R^2 = 0.3008$; $p < 0.001$), indicating a moderate association between general openness toward AI in healthcare and attitudes toward conversational AI specifically. Respondents with more positive attitudes toward AI applications in healthcare also tended to evaluate ChatGPT more positively. However, the explanatory power of the model remained moderate, suggesting that ChatGPT-related attitudes are influenced by additional factors beyond general technological openness. These findings indicate that competence-related variables alone are insufficient to explain trust in conversational AI systems. Despite relatively high levels of digital health literacy, respondents remained cautious toward AI-generated health information. This supports Hypothesis 2 and reinforces the distinction between competence and trust identified throughout the earlier analyses.

At the same time, the moderate relationship between general healthcare AI attitudes and ChatGPT-related attitudes provides support for Hypothesis 3 by suggesting that positive evaluations of AI usefulness are associated with more favourable perceptions of conversational AI.

Finally, the generally low explanatory power of most regression models supports Hypothesis 5 by indicating that traditional UTAUT-related predictors explain only a limited proportion of variance in ChatGPT-related attitudes. Trust, perceived risk, and role-based interpretation therefore appear to function as additional explanatory dimensions.

6.7 Results of the representative 40+ survey

To complement the primary student-based dataset, a representative survey was conducted among Hungarian adults aged 40 years and above (N = 200). The purpose of this complementary dataset was to examine whether the patterns identified in the younger sample also appear among older population groups, particularly in relation to trust, behavioural intention, and role-based acceptance of ChatGPT in healthcare contexts.

The survey applied the same five ChatGPT-related items used in the primary dataset, although responses were measured on a 4-point forced-choice scale (1 = totally agree, 4 = totally disagree) without a neutral midpoint. This design was intended to encourage clearer directional responses and reduce neutral positioning. Table 29 summarizes the descriptive results of the representative 40+ survey.

Table 29: 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 medical professiona l.	Statement 4 I would rather go to ChatGPT with uncomforta ble, overly personal questions than see a medical professional 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

Overall, the results indicate a cautious orientation toward ChatGPT in healthcare contexts. Trust in ChatGPT as a medical information source remained limited, while skepticism was particularly strong regarding the replacement of medical professionals. (Longoni et al., 2019; Glikson and Woolley, 2020).

At the same time, respondents evaluated the broader societal usefulness of ChatGPT more positively, especially regarding access to information and health literacy. Expectations regarding future healthcare integration also remained relatively high despite persistent trust-related concerns.

Similar to the student sample, respondents differentiated clearly between supportive and substitutive AI roles. Acceptance was substantially higher for informational and assistive functions than for replacement-oriented healthcare applications.

Gender differences within the representative sample were relatively small and statistically non-significant. Male respondents consistently reported slightly more positive evaluations across most items, but the magnitude of these differences remained limited. Table 30 presents gender differences across the five ChatGPT-related items.

Table 30: 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

Although weaker than in the student sample, the direction of the effect remained consistent across both datasets, with male respondents generally expressing somewhat higher levels of openness toward conversational AI.

More substantial variation emerged across generations. Respondents in their early 40s displayed the highest levels of acceptance across most indicators, while Baby Boomers consistently expressed greater skepticism. Table 31 presents descriptive statistics across generational groups.

Table 31: 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 medical professional.**	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 medical professional 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 strongest differences appeared in relation to behavioural substitution and the use of ChatGPT for sensitive or personal questions. Agreement with asking health-related questions to ChatGPT more often than to medical professionals declined from 45% among Millennials to 15% among Baby Boomers.

In contrast, broader perceptions regarding societal usefulness and future healthcare integration remained comparatively stable across generations. Table 32 summarizes the statistical significance of the observed generational differences.

Table 32: 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 medical professional.	Highest mean (2.57) (SD=1.02)	Lower mean (3.12) (SD=0.94)	Lower 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 medical professional 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 indicate higher acceptance/trust (1=totally agree, 4=totally disagree)
Source: Author's own data collection

The results confirm that generational effects are selective rather than universal. Significant differences emerged primarily for behavioural substitution and sensitive-topic use, while broader evaluations of reliability and future integration showed no significant variation.

These findings support Hypothesis 1 and Hypothesis 4 by indicating that age influences behavioural willingness to engage with conversational AI, while supportive AI roles remain more accepted than substitutive ones across generations.

6.7.1 Comparison between the student and representative 40+ samples

Before directly comparing the two empirical datasets, it is important to acknowledge their methodological differences. The primary student survey applied a 5-point Likert scale, while the representative 40+ survey used a 4-point forced-choice format without a neutral midpoint. In addition, the datasets differ substantially in sampling strategy, demographic composition, and analytical purpose.

Consequently, the following comparison is interpretative rather than strictly statistical. The aim is not to directly compare mean values across incompatible scales, but rather to identify broader structural patterns that appear consistently across both datasets. Table 33 summarizes the main comparative patterns.

Table 33: Comparison of ChatGPT-related attitudes across the two datasets (standardized 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 medical professionals 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 (Δ ≈ 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 emerged across both datasets. First, replacement of medical professionals by ChatGPT was clearly rejected in both samples. Even among younger and digitally experienced respondents, willingness to substitute traditional medical consultation remained low.

Second, trust in ChatGPT was lower and more clearly bounded in the representative 40+ sample, whereas the student sample showed greater variability and openness toward experimentation.

Third, age-related differences were considerably stronger in the representative dataset. Younger cohorts consistently expressed greater openness toward conversational AI, particularly regarding behavioural use and sensitive topics.

Finally, both datasets showed relatively high expectations regarding the future integration of ChatGPT into healthcare despite persistent trust-related concerns.

Overall, the comparison reinforces the interpretation that AI acceptance in healthcare is conditional and role-dependent. Across both datasets, respondents were substantially more willing to accept conversational AI in supportive rather than substitutive healthcare functions. These findings provide additional support for Hypothesis 1, Hypothesis 4, and Hypothesis 5.

6.8 Digital health use and trust in Hungary: contextual interpretation

To place the empirical findings into a broader societal context, the dissertation integrates secondary statistical indicators related to digital health behaviour, digital competence, trust in digital health services, and attitudes toward AI-supported healthcare in Hungary and the European Union.

The purpose of this contextual analysis is not to directly validate the primary survey results, but rather to examine whether broader population-level tendencies correspond to the patterns identified in the empirical datasets. This triangulated approach strengthens interpretability by linking micro-level attitudinal findings to wider structural trends observed in national and international datasets (OECD, 2022; Eurostat, 2023).

The secondary indicators presented in Chapter 3 revealed a consistent gap between digital engagement and trust-related indicators. The present contextual interpretation demonstrates that a similar pattern emerged in the empirical datasets. Although respondents reported relatively high levels of digital health literacy and digital engagement, trust toward ChatGPT-related healthcare use remained substantially lower. This convergence across datasets supports the interpretation that competence and trust represent partially independent dimensions in healthcare AI acceptance.

This distinction is particularly important in the context of generative AI. Traditional digital health literacy primarily concerns searching for, evaluating, and applying online information (Norman and Skinner, 2006). Conversational AI systems, however, introduce additional concerns related to transparency, accountability, and reliability, meaning that competence alone may be insufficient to generate trust (Shin, 2021).

The consistency across datasets is analytically important because it suggests that skepticism toward AI in healthcare is not merely a sample-specific phenomenon. Cultural and innovation-related differences across European societies may also influence national attitudes toward emerging technologies, including AI-supported healthcare systems (Végh et al., 2025). Instead, concerns regarding reliability, accountability, and risk appear to represent broader societal patterns extending beyond individual demographic groups. This interpretation aligns with previous research emphasizing that trust plays a particularly central role in healthcare AI adoption because medical contexts involve high levels of uncertainty and perceived personal risk (Glikson and Woolley, 2020; Shin, 2021). The consistency of this pattern across all datasets is broadly consistent with Hypothesis 4, according to which acceptance of ChatGPT is conditional and role-dependent.

Importantly, this finding also supports the broader theoretical interpretation that acceptance of AI in healthcare cannot be explained solely through traditional UTAUT variables such as usefulness or ease of use. Instead, perceived professional role and trust-related boundaries appear to represent additional explanatory dimensions.

To improve comparability across the different datasets, selected indicators were standardized and compared directly. Table 34 presents the comparison across data sources.

Table 34: Comparison of digital competence and AI attitudes across data sources (%, N varies 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 medical professionals	< 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.

Several stable regularities emerge from the triangulated comparison. First, high digital engagement consistently coexists with lower trust across all datasets. Even among digitally active respondents, trust-related indicators remain substantially lower than competence indicators. Second, substitution of healthcare professionals by AI is consistently rejected across all data sources. Despite differences in sample composition and methodology, acceptance of replacement functions remains clustered within a relatively narrow low range. Third, expectations regarding future AI integration remain relatively high across all groups. This indicates that respondents distinguish between present trust and future technological expectations. This divergence is analytically important because it demonstrates that skepticism toward current AI systems does not necessarily imply rejection of long-term technological integration.

The representative 40+ dataset further strengthens this interpretation by functioning as an intermediate analytical layer between macro-level secondary indicators and the younger student sample.

Secondary statistics consistently show strong age-related gradients in both digital health engagement and trust toward AI systems. The representative survey reproduces these generational patterns quantitatively.

Respondents in their early 40s display acceptance levels considerably closer to the student sample, whereas Baby Boomers consistently express lower trust and stronger rejection of substitution-related AI roles.

This gradual decline across generations suggests that AI acceptance in healthcare follows a continuum rather than a binary division between younger and older populations. Table 39 compares trust and behavioural intention indicators across the three major data sources.

Despite methodological differences, the convergence of results is striking. Across datasets: trust indicators remain relatively moderate or low; substitution-related acceptance remains consistently limited; expectations regarding future integration remain comparatively high. These recurring patterns considerably strengthen the robustness of the dissertation’s findings because similar structural tendencies appear repeatedly across independent datasets and methodological approaches (Table 35).

Table 35: 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 medical professional 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.

Taken together, the contextual interpretation confirms that acceptance of AI in healthcare is shaped by the interaction of competence, trust, and role perception. The results indicate that digital competence may facilitate engagement with AI-supported systems, but it does not eliminate concerns related to reliability, accountability, and professional legitimacy. At the same time, respondents across generations increasingly perceive AI integration into healthcare systems as likely or inevitable, even while maintaining clear boundaries regarding acceptable use. The triangulated findings therefore provide strong contextual support for Hypothesis 2, Hypothesis 4, and Hypothesis 5. More broadly, they reinforce the conclusion that traditional technology acceptance frameworks require extension in healthcare AI contexts, where trust and perceived technological role play a central explanatory function alongside classical UTAUT predictors (Venkatesh et al., 2003; Glikson and Woolley, 2020; Shin, 2021).

The results presented in this chapter provide the empirical basis for evaluating the dissertation's hypotheses. The integrated assessment of the hypotheses is presented in Chapter

7, where the findings from the student survey, the representative 40+ dataset, and secondary statistical indicators are interpreted together.

7. CONCLUSIONS AND RECOMMENDATIONS

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

This section evaluates the five hypotheses of the dissertation by integrating findings from the primary student survey, the representative 40+ dataset, and the secondary statistical indicators. Table 36 summarizes the operationalisation, analytical methods, and outcomes of the five hypotheses.

Table 36: Integrated summary of hypothesis evaluation and theoretical implications

Hypothesis	Research focus	Main measures	Analysis	Result	Contribution
H1	Demographic differences in ChatGPT acceptance	Age, gender, education; ChatGPT scale; 40+ generational items	t-test, ANOVA, subgroup comparison	Partially supported: gender significant in student sample ($p = 0.0006$); generational effects significant in 40+ sample for substitution ($p = 0.05$) and sensitive use ($p = 0.02$); education not significant for ChatGPT trust	Shows that demographic effects are selective and construct-specific
H2	Competence–trust gap	eHEALS and ChatGPT scale	Standardized comparison, regression	Supported: eHEALS reached 72%, ChatGPT scale 51%; eHEALS explained only 6.76% of ChatGPT variance ($R^2 = 0.0676$, $p < 0.001$)	Demonstrates that digital health literacy and trust in AI are distinct constructs
H3	Trust, usefulness and behavioural intention	ChatGPT items, AI attitude scale	Regression and item-level interpretation	Supported: AI/robot attitude scale explained 30.08% of ChatGPT attitudes ($R^2 = 0.3008$, $p < 0.001$)	Confirms the central role of trust-related AI attitudes in ChatGPT acceptance
H4	Supportive vs substitutive acceptance	ChatGPT item 3; 40+ substitution item; secondary data	Item-level and cross-dataset comparison	Strongly supported: substitution was rejected in both samples; 78% of 40+ respondents rejected asking ChatGPT instead of professionals; secondary data show only 22–26% support AI replacement	Establishes role-based acceptance as a core explanatory dimension
H5	Need to extend UTAUT	Regression, triangulation, secondary data	Integrated interpretation	Supported: traditional predictors explain only limited variance; trust, risk and role perception remain central	Supports a trust- and role-sensitive extension of UTAUT for healthcare AI

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).

Hypothesis 1 proposed that demographic characteristics, particularly age, gender, and education, are associated with differences in attitudes and behavioural intention to use ChatGPT in healthcare contexts. The findings partially support this hypothesis. The strongest demographic effects emerged for gender and age. Male respondents reported more positive attitudes toward ChatGPT, while acceptance decreased across older generations, particularly regarding behavioural substitution and the use of ChatGPT for sensitive health-related questions. In contrast, education showed a strong relationship with digital health literacy and emotional attitudes toward automation, but not with ChatGPT-specific trust. These findings suggest that demographic effects are selective rather than universal, and that different demographic variables influence different dimensions of AI acceptance.

Hypothesis 2 proposed that digital health literacy is not a strong predictor of trust in ChatGPT, indicating a gap between competence and trust in digital health contexts. The findings strongly support this hypothesis. Although respondents reported relatively high levels of digital health literacy, attitudes toward ChatGPT remained considerably more cautious. Regression analyses demonstrated only weak relationships between eHEALS scores and ChatGPT-related attitudes, indicating a competence–trust gap. Secondary statistical indicators reproduced the same structural pattern at the population level: digital health engagement remained high, while trust in AI-supported healthcare tools remained substantially lower. These findings suggest that trust represents a partially independent dimension shaped not only by competence, but also by perceived reliability, uncertainty, accountability, and risk.

Hypothesis 3 proposed that more positive trust-related attitudes toward healthcare AI are associated with more positive attitudes and behavioural intention toward ChatGPT use in healthcare contexts. The findings support this hypothesis. Respondents who evaluated ChatGPT more positively also reported stronger perceived usefulness and greater openness toward AI-supported healthcare functions. However, the findings also indicate that perceived usefulness alone is insufficient to generate strong adoption intentions in healthcare contexts. Respondents frequently acknowledged the potential societal usefulness of ChatGPT while remaining hesitant regarding personal use. This suggests that trust functions as an important mediating mechanism between perceived usefulness and behavioural intention.

Hypothesis 4 proposed that acceptance of ChatGPT in healthcare is conditional: users are more willing to accept it as a supportive tool than as a substitute for medical professionals. This hypothesis received the strongest empirical support across all datasets. Respondents consistently expressed greater openness toward informational and supportive AI functions than toward replacing medical professionals or autonomous medical decision-making. This pattern remained stable across demographic groups and data sources, indicating that acceptance of healthcare AI is role-sensitive rather than absolute.

Hypothesis 5 proposed that traditional UTAUT predictors are insufficient to fully explain acceptance of AI in healthcare, as trust and role-based perceptions play an additional role. The findings support this hypothesis. Competence-related variables showed limited explanatory power regarding trust and behavioural intention, while acceptance appeared strongly influenced by trust, perceived reliability, and role-based interpretation. These findings suggest that healthcare AI adoption cannot be fully explained through traditional technology acceptance variables alone, and that trust-sensitive extensions of UTAUT and TAM frameworks are required in healthcare AI contexts.

The integrated interpretation of the findings demonstrates that conversational AI acceptance in healthcare is conditional, trust-sensitive, and role-dependent rather than uniformly technology-driven.

Across all datasets, respondents consistently distinguished between supportive and substitutive AI roles. While informational and assistive use cases received relatively positive evaluations, replacement-oriented functions involving professional medical responsibility were rejected across generations and demographic groups.

The results also revealed a clear competence–trust gap. Although respondents demonstrated relatively high digital health literacy, trust in ChatGPT-related healthcare use remained substantially lower. This suggests that competence and trust represent partially independent dimensions in healthcare AI acceptance.

At the same time, the findings indicate that traditional UTAUT-related variables alone are insufficient to explain conversational AI acceptance in healthcare. Trust, perceived risk, and role-based legitimacy emerged as central explanatory mechanisms.

7.2 Implications for TAM and UTAUT

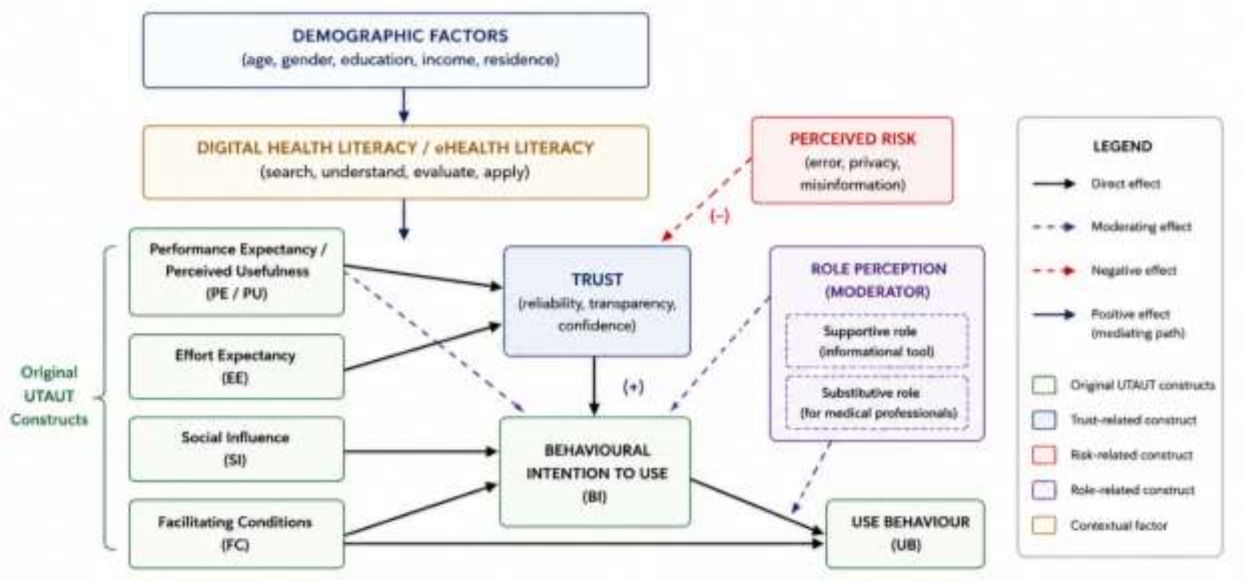
The findings confirm that TAM and UTAUT remain useful theoretical starting points for analysing ChatGPT acceptance in healthcare. Constructs such as perceived usefulness, behavioural intention, and demographic moderation remain relevant. However, the results also indicate that traditional technology acceptance models require contextual extension when applied to generative AI in healthcare settings.

Regression analyses demonstrated that general healthcare AI attitudes were moderately associated with ChatGPT-related attitudes ($R^2 = 0.3008$, $p < 0.001$), while digital health literacy explained only a limited share of ChatGPT acceptance ($R^2 = 0.0676$, $p < 0.001$). These findings indicate that competence and usefulness alone cannot fully explain trust in conversational AI systems.

The results further showed that respondents consistently accepted ChatGPT more readily as a supportive informational tool than as a substitute for medical professionals. This role-based boundary is not fully captured by traditional UTAUT constructs. Trust, perceived risk, and role perception therefore emerged as central explanatory dimensions in healthcare AI acceptance.

Accordingly, the research proposes a trust- and role-sensitive extension of UTAUT for generative AI in healthcare. In the proposed model, trust functions as a mediating mechanism between perceived usefulness and behavioural intention, while perceived risk weakens trust and thereby reduces willingness to use AI-supported healthcare tools. Role perception moderates acceptance by influencing whether ChatGPT is interpreted as a supportive informational assistant or as a substitute for healthcare professionals. Acceptance is therefore expected to be stronger when ChatGPT is perceived as a supportive tool and weaker when it is perceived as a substitute for healthcare professionals. Figure 7 presents the proposed trust- and role-sensitive extension of UTAUT for generative AI in healthcare.

Figure 7: Trust- and role-sensitive extension of UTAUT for generative AI in healthcare



Source: Author's own construction based on Venkatesh et al. (2003), Glikson and Woolley (2020), Shin (2021), and the empirical findings of the dissertation

7.3 Recommendations

Based on the findings, ChatGPT and similar conversational AI tools should be positioned explicitly as supplementary resources rather than substitutes for healthcare professionals. This recommendation is strongly supported by the data: 78% of respondents in the representative 40+ sample rejected asking ChatGPT health questions more often than a medical professional, and secondary indicators show that only 22–26% support AI replacing healthcare professionals.

Healthcare institutions should therefore focus on low-risk, supportive applications, such as patient education, explanation of medical terminology, preparation for consultations, and post-consultation clarification. These use cases correspond to the role respondents were more willing to accept.

Communication strategies should also be differentiated by demographic group. Younger users may need stronger AI literacy and critical evaluation skills, as high digital familiarity does not automatically imply appropriate trust. Older users may require clearer reassurance regarding human oversight, reliability, data protection, and accountability. Middle-aged respondents, especially those in their early 40s, showed relatively higher openness in the representative dataset, suggesting that practical usefulness and relevance to real healthcare needs may be especially important for this group.

Policy recommendations should focus on certification, quality assurance, transparency, and professional oversight. Since trust is central to acceptance, AI-based health tools are more likely to be accepted if they are embedded in regulated healthcare environments rather than presented as independent substitutes for medical expertise. Clear guidelines on appropriate use, liability, explainability, and data protection are therefore necessary for sustainable implementation.

Healthcare professionals also have an important mediating role. Professional endorsement and clear guidance could increase acceptance while preserving the boundaries between AI-supported information and medical decision-making.

7.4 Limitations

Several limitations must be acknowledged. The primary survey was conducted among Hungarian university students (N = 172), resulting in a young, educated, and digitally experienced sample. This limits generalizability to the broader Hungarian population. Age-related effects were also difficult to detect in this dataset because of the restricted age range.

This limitation was partly addressed through the representative 40+ dataset (N = 200), which allowed generational patterns to be examined more robustly. However, the two datasets used different sampling strategies and response scales, so direct statistical comparison was not possible. Their comparison should therefore be interpreted as pattern-based rather than as direct numerical equivalence.

Another limitation concerns measurement. eHEALS and NARS are validated scales, but the AI/robot and ChatGPT-specific items were self-developed. Although they were theoretically grounded in TAM and UTAUT, the 8-item healthcare AI scale showed low internal consistency (Cronbach's $\alpha = 0.432$), suggesting a multidimensional construct. The ChatGPT scale showed acceptable reliability ($\alpha = 0.787$), but further validation would strengthen future research.

The analysis relied mainly on descriptive statistics, group comparisons, and regression analyses. These methods are appropriate for exploratory hypothesis testing, but they do not allow causal inference. Future research could apply structural equation modelling or moderation analysis to test the proposed trust- and role-sensitive UTAUT extension more directly.

Finally, the study captures attitudes during an early phase of generative AI adoption. Public perceptions of ChatGPT may change as AI tools improve, regulatory frameworks develop, and users gain more direct experience with AI-supported healthcare systems.

8. NEW SCIENTIFIC RESULTS

Based on the empirical analyses conducted in this dissertation, the following new scientific results can be identified regarding the acceptance of ChatGPT in healthcare contexts in Hungary. The following scientific results are derived from the integrated interpretation of the hypothesis testing, triangulated empirical analyses, and secondary contextual indicators presented in the dissertation.

1. **Acceptance of ChatGPT in healthcare is conditional and strongly role-dependent**.
   Across all analysed datasets, respondents showed substantially higher acceptance of ChatGPT as a supportive informational tool than as a substitute for healthcare professionals. This demonstrates that public acceptance of healthcare AI is shaped not only by perceived usefulness, but also by perceived professional role boundaries.
2. **Substitutive healthcare use of ChatGPT is consistently rejected across demographic groups and datasets**.
   In the representative 40+ sample, 78% of respondents rejected asking ChatGPT health-related questions more frequently than medical professionals, while secondary indicators showed that only 22–26% support AI replacing healthcare professionals.
3. **Digital health literacy and trust in ChatGPT represent analytically distinct dimensions**.
   Although respondents demonstrated relatively high levels of digital health literacy (eHEALS standardized value: 72%), attitudes toward ChatGPT in healthcare remained substantially lower (standardized value: 51%), indicating a clear competence–trust gap.
4. **Digital competence explains only a limited proportion of variance in ChatGPT-related healthcare acceptance**.
   Regression analysis demonstrated that eHEALS explained only 6.76% of the variance in ChatGPT attitudes ($R^2 = 0.0676$, $p < 0.001$), suggesting that trust formation in healthcare AI contexts cannot be sufficiently explained by competence-related variables alone.
5. **Generational differences in ChatGPT acceptance are selective and most pronounced in behavioural use contexts.**

Significant differences emerged regarding substitutive healthcare use ($p = 0.05$) and the use of ChatGPT for sensitive health-related topics ($p = 0.02$), while expectations concerning future AI integration into healthcare remained comparatively stable across generations.

6. **Based on the empirical findings, the dissertation proposes a trust- and role-sensitive extension of UTAUT for generative AI in healthcare contexts.**
   The results indicate that traditional UTAUT variables alone cannot fully explain acceptance of ChatGPT in healthcare. In addition to classical acceptance factors, trust, perceived risk, and role perception emerged as central explanatory dimensions shaping behavioural intention and willingness to use AI-supported health communication tools.

APPENDICES

Appendix I: References

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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.

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