Portrayals of Artificial Intelligence (AI): Assessing patient reliance in high-risk medical decision-making

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Abstract

Title: Portrayals of Artificial Intelligence (AI): Assessing patient reliance in high-risk medical decision-making

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As healthcare increasingly adopts artificial intelligence (AI) for decision support, the success of AI systems depends on user trust and willingness to rely on recommendations, especially in high-risk medical scenarios. This study used an experiment featuring different portrayals of AI—presented as code-based, morph, or human-like—to assess how these visual representations impact patients' trust in AI recommendations. The findings reveal that visual portrayals of AI has no significant effect on utilitarian motivation, interaction convenience, or task-technology fit. Instead, perceived competence emerges as the most influential factor in building trust, which in turn increases reliance on AI recommendations.

The results highlight that users prioritize the functional competence and reliability of AI over aesthetic or anthropomorphic features, particularly when accuracy and trust are critical. The study offers important managerial insights for organizations integrating AI systems, emphasizing the need for transparency, accuracy, and reliability to foster trust. While aesthetic enhancements may attract initial engagement, they should not detract from delivering clear and reliable outputs.

By focusing on competence and trustworthiness, organizations can enhance AI adoption, particularly in healthcare, where accurate decision support is crucial. This research underscores the importance of designing AI systems that not only meet technical standards but also maintain user trust, ensuring their effective use in decision-making processes.

Keywords: Artificial Intelligence (AI), AI Acceptance, Healthcare Decision-Making, Patient Reliance, Trust in AI, Technology Adoption

Sumário

Titlulo: Retratos da Inteligência Artificial (IA): Avaliando a confiança dos pacientes na tomada de decisões médicas de alto risco

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À medida que a área da saúde adota a inteligência artificial (IA) para apoio à decisão, o sucesso dos sistemas de IA depende da confiança dos utilizadores e da sua disposição em seguir as recomendações, especialmente em cenários médicos de alto risco. Este estudo utilizou um experimento com diferentes representações visuais de IA — baseadas em código, forma morfa ou semelhantes a humanos — para avaliar o impacto na confiança dos pacientes nas recomendações de IA. Os resultados mostram que a forma visual da IA não afeta significativamente a motivação utilitária, a conveniência da interação ou a adequação tarefa-tecnologia. Em vez disso, a perceção de competência é o fator mais relevante na construção de confiança, aumentando a aceitação das recomendações de IA.

Os resultados salientam que os utilizadores valorizam a competência funcional e a fiabilidade da IA em vez de características estéticas ou antropomórficas, especialmente quando a precisão e a confiança são essenciais. O estudo oferece insights para a gestão de organizações que integram IA, sublinhando a importância da transparência, precisão e fiabilidade para promover a confiança. Embora melhorias estéticas possam atrair atenção inicial, estas não devem comprometer a entrega de resultados claros e fiáveis.

Ao focar-se na competência e na confiança, as organizações podem facilitar a adoção da IA, particularmente no setor da saúde, onde o apoio preciso à decisão é fundamental. Esta investigação destaca a importância de projetar sistemas de IA que cumpram padrões técnicos e preservem a confiança dos utilizadores.

Palavras-chave: Inteligência Artificial (IA), Aceitação da IA, Tomada de Decisões em Saúde, Confiança dos Pacientes, Confiança na IA, Adoção de Tecnologia

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Glossary

α	Cronbach's alpha
AI	Artificial Intelligence
AIDUA	Artificially Intelligent Device Use Acceptance
ANOVA	Analysis of Variance
β	Regression coefficient
CDSS	Clinical Decision Support System
F	F-statistic
H1	Hypothesis 1 (2-8 respectively)
IC	Interaction Convenience
M	Sample mean
MANOVA	Multivariate Analysis of Variance
N	Total number of cases
p	p-value
PC	Perceived Competence
r	Pearson correlation Effect
R^2	Multiple correlation squared, measure of strength of association
SD	Standard Deviation
TAI	Trustworthy Artificial Intelligence
TAM	Technology Acceptance Model
TTF	Task-Technology Fit
UTAUT	Unified Theory of Acceptance and Use of Technology
UM	Utilitarian Motivation

WOA	Weight on Advice
XAI	Explainable AI

1 Introduction

1.1 Opening Thought

Artificial intelligence (AI) is transforming healthcare by enhancing patient care and decision-making processes (Davenport & Kalakota, 2019). Applications of AI, including clinical decision support systems, predictive modeling, and personalized treatment plans, are revolutionizing how healthcare professionals diagnose, treat, and monitor patients (D. Lee & Yoon, 2021; E. J. Topol, 2019). These technologies offer efficient solutions that improve decision-making, diagnosis, prognosis, and treatment processes (Gulshan et al., 2016). By leveraging AI, healthcare professionals can access more precise data, enabling better patient decisions and predictive models for long-term monitoring (Secinaro et al., 2021). The integration of AI in healthcare not only streamlines processes but also facilitates personalized and proactive disease management, leading to improved patient outcomes and more effective interventions (Chen & Decary, 2020; Yu et al., 2018).

1.2 Relevance of the topic

The relevance of AI in healthcare has become increasingly prominent as the industry faces significant challenges, including escalating costs, the need for personalized care, and the demand for more efficient healthcare delivery (Meskó et al., 2017). AI technologies offer innovative solutions that address these challenges by enhancing diagnostic accuracy, optimizing treatment plans, and improving patient monitoring (Obermeyer & Emanuel, 2016).

Recent studies have shown that AI can outperform traditional diagnostic methods, offering greater precision and reducing the likelihood of human error (Litjens et al., 2017). Moreover, AI-driven tools are increasingly being used to predict patient outcomes, allowing for more proactive and personalized care (Poalelungi et al., 2023). However, the adoption of AI in healthcare is not without challenges. The acceptance and trust in AI systems are crucial, particularly in high-stakes medical environments where decisions can have life-altering consequences (Goddard et al., 2012).

Given the increasing reliance on AI for critical healthcare decisions, it is essential to understand how different portrayals of AI—such as code-based, morph, or human-like—affect patient trust and reliance on these systems (Ghassemi et al., 2020; Goddard et al., 2012). This is particularly important as healthcare continues to integrate AI into clinical workflows, where patient trust and acceptance are vital for the successful implementation of these technologies (Cabitza et al., 2017; He et al., 2019). This study will contribute to the existing body of knowledge by examining these dynamics, providing insights that are essential for the future of AI in healthcare. The findings will help shape the development and deployment of AI systems, ensuring they meet the needs of both patients and healthcare professionals (Holzinger et al., 2018; Shortliffe & Sepúlveda, 2018).

1.3 Problem Statement and Research Objective

There is increasing interest in how AI can bridge the gap between human decision-making and automated systems (Jarrahi, 2018). Research shows that while algorithms often outperform human judgment, people remain hesitant to rely on them, a phenomenon known as algorithm aversion (Dawes, 2008). This skepticism often stems from overconfidence in personal judgments and a tendency to undervalue external advice (Yaniv & Kleinberger, 2000).

Conversely, recent studies have demonstrated a growing appreciation for algorithmic advice, especially when algorithms are perceived as more reliable than human judgment (Logg et al., 2019). Trust in AI is crucial in this context, as individuals are more likely to rely on AI when they trust its capabilities and outputs (J. D. Lee & See, 2004).

However, there is limited research comparing responses to AI-generated advice versus human advice. This gap is particularly important as healthcare increasingly integrates AI into decision-making to mitigate human biases. This research aims to explore how different portrayals of AI—whether as code-based, morph, or human-like—affect patient reliance on AI advice, particularly in high-risk medical situations and seeks to answer the following research questions:

How do portrayals of AI as code-based, morph, and human-like influence patient reliance on AI advice for high-risk medical decisions?

What factors explain a possible relationship between AI portrayals and reliance on AI advice? Specifically, what is the role of utilitarian motivation, interaction convenience, task-technology fit, perceived competence, and trust?

This study will employ an experimental method to examine how different AI portrayals influence patient reliance on AI advice. Understanding these dynamics is essential for improving the implementation and acceptance of AI in healthcare, thereby contributing to more effective decision-making processes. This investigation is crucial for the successful integration of AI in healthcare, as it heavily depends on patient trust and acceptance.

1.4 Structure of the dissertation

This dissertation is structured to systematically address the research questions on AI portrayals and their impact on patient reliance in healthcare. Chapter 1 introduces the topic, outlines the problem statement, and presents the research questions and objectives. Chapter 2 reviews existing literature on AI in healthcare, theoretical frameworks, and studies on AI portrayals, establishing the basis for the research hypotheses. Chapter 3 describes the research design, data collection, and analysis methods, ensuring reliability and validity. Chapter 4 interprets the results, discusses theoretical and practical implications, and addresses limitations. Finally, Chapter 5 summarizes the key findings, highlights contributions to the field, discusses practical implications, and suggests directions for future research.

2 Literature Review

This chapter reviews the theoretical foundations for AI acceptance in healthcare, focusing on decision-making, reliance, trust, anthropomorphic features, and AI portrayals. The discussion is framed within the Technology Acceptance Model (TAM) and its adaptation, the Artificially Intelligent Device Use Acceptance (AIDUA) model. Hypotheses related to utilitarian motivation, interaction convenience, and task-technology fit are introduced systematically, culminating in a comprehensive conceptual framework.

2.1 AI in Healthcare: An Overview

2.1.1 Evolution and Integration of AI in Healthcare

AI has steadily evolved over the past few decades, transforming healthcare by enhancing decision-making, diagnostics, and treatment processes (E. J. Topol, 2019). The integration of AI into healthcare has been driven by its ability to process vast amounts of data quickly and accurately, offering predictive modeling and data analysis that uncover patterns and actionable insights (Reddy et al., 2019; Secinaro et al., 2021). AI-driven Clinical Decision Support Systems (CDSS) reduce cognitive biases and errors, leading to more reliable medical decisions (Jiang et al., 2017; D. Lee & Yoon, 2021). Notably, AI has significantly improved diagnostic precision in medical imaging, detecting anomalies with greater accuracy than human observers (Rajpurkar et al., 2018; E. J. Topol, 2019).

The integration of AI extends beyond diagnostics to personalized medicine, where AI incorporates patient-specific data—such as genetics, lifestyle, and comorbidities—to develop tailored treatment plans (Davenport & Kalakota, 2019). Moreover, AI automates routine tasks, such as administrative work, thereby increasing efficiency and reducing healthcare staff workloads (Reddy et al., 2019). The ongoing development of AI technologies is crucial for maintaining and improving precision and reliability in healthcare applications, from genomics to robotic surgery (Hashimoto et al., 2018; E. Topol, 2019).

2.1.2 Current Applications of AI in Healthcare

AI's current applications in healthcare span several domains, each contributing to improved accuracy, efficiency, and patient outcomes (Jiang et al., 2017). In diagnostics, AI systems have outperformed radiologists in identifying conditions such as skin lesions and pulmonary nodules, achieving high precision and speed (Tschandl et al., 2020). In predictive analytics, AI forecasts patient outcomes and disease progression by analyzing large datasets, significantly enhancing early intervention strategies (Miotto et al., 2018; Tomašev et al., 2019).

Furthermore, AI's role in personalized medicine allows for treatment plans tailored to individual patient needs, optimizing outcomes and reducing adverse effects (Beam & Kohane, 2018; Wang et al., 2019). AI-equipped wearable devices continuously monitor patient vitals, improving chronic disease management and enabling timely interventions (Avram et al., 2019; Dunn et al., 2018). Additionally, AI enhances operational efficiency by automating tasks such as scheduling, billing, and patient triage, reducing the administrative burden on healthcare staff (Jiang et al., 2017). In surgical applications, AI supports robotic surgery, enabling precise and minimally invasive procedures that reduce recovery times and complications (Hashimoto et al., 2018).

2.2 AI in Decision-Making

2.2.1 Enhancing Decision Accuracy with AI

AI has proven to significantly enhance decision-making accuracy in healthcare by augmenting human capabilities and addressing cognitive limitations (Amann et al., 2020). By reducing biases in diagnostics and providing consistent, data-driven insights, AI leads to improved patient outcomes (Amann et al., 2020; Maron, 2022). AI algorithms analyze patient records and imaging data to identify patterns that clinicians might miss, thereby increasing the accuracy of diagnoses and treatment plans (Obermeyer & Emanuel, 2016). For instance, deep learning models have demonstrated dermatologist-level accuracy in classifying skin cancer, underscoring AI's potential in enhancing diagnostic precision (Brinker et al., 2019). AI also synthesizes data from multiple sources to offer evidence-based recommendations, addressing cognitive biases such as confirmation bias (Rajkomar et al., 2019). This capability is particularly crucial in clinical decision support, where accurate and unbiased decisions are vital for patient care. AI's role in forecasting patient outcomes and disease progression further highlights its importance in proactive healthcare management (Gulshan et al., 2016; Liu et al., 2019).

2.2.2 The Role of AI in Clinical Decision Support

In clinical settings, AI enhances decision-making by providing real-time, evidence-based recommendations. AI's ability to integrate diverse data sources and analyze large datasets enables healthcare providers to make more informed decisions across medical specialties (E. Topol, 2019). AI's contribution to clinical decision support systems is particularly valuable in complex cases where multiple factors must be considered simultaneously. For example, AI-driven systems help clinicians develop personalized treatment plans by analyzing genetic and lifestyle data, leading to improved patient outcomes (Jensen et al., 2021; Shah et al., 2019).

Furthermore, AI mitigates common cognitive biases, such as availability and anchoring biases, by offering objective, data-driven insights (Rajkomar et al., 2019). This unbiased approach to decision-making is essential in healthcare, where the accuracy of diagnoses and treatments can have life-altering consequences. The integration of AI into clinical decision support not only improves decision accuracy but also enhances the overall quality of patient care (Maron, 2022; Sendak et al., 2020).

2.3 Reliance on AI Advice

Reliance on AI-generated advice is increasingly significant in healthcare as AI systems become integral to clinical decision-making and for AI to be effectively integrated, healthcare professionals must trust and rely on its recommendations (Jiang et al., 2017; E. Topol, 2019). Trust plays a central role in determining the extent to which healthcare providers incorporate AI advice into their decision-making processes and is closely linked to the perceived competence, transparency, and reliability of the AI system (Glikson & Woolley, 2020; Hoff & Bashir, 2015). When healthcare professionals perceive an AI system as competent and trustworthy, they are more likely to depend on its recommendations, especially in high-stakes scenarios where accurate and timely decisions are crucial (Mittelstadt, 2019).

2.3.1 Building Trust in AI: Key Determinants

Trust in AI systems is shaped by several factors, with perceived competence being particularly important (Glikson & Woolley, 2020). Perceived competence refers to the belief that the AI system can perform its intended tasks accurately and effectively (Hoff & Bashir, 2015). Healthcare professionals are more likely to trust and rely on AI-generated advice if they believe the system is capable and reliable (Dzindolet et al., 2003; Miotto et al., 2018). For instance, AI systems that demonstrate consistent accuracy in diagnostic tasks or patient outcome predictions are viewed as more trustworthy by clinicians (E. Topol, 2019; Tschandl et al., 2019).

Transparency is another critical factor influencing trust, as AI systems that provide clear and understandable explanations for their recommendations are more likely to gain the trust of healthcare providers (Chen & Decary, 2020; Ribeiro et al., 2016). Transparency enables users to comprehend how and why specific decisions are made, aligning AI recommendations with clinical knowledge and expectations (Eiband et al., 2018; Nunes & Jannach, 2017). If an AI system can clearly articulate the reasoning behind a treatment recommendation, healthcare providers are more likely to trust and follow that advice, as it resonates with their clinical reasoning (Wang et al., 2019).

Reliability, defined as the consistency and accuracy of the AI system across different cases and over time, also plays a significant role in fostering trust (J. D. Lee & See, 2004). Healthcare providers are more inclined to depend on AI advice if the system consistently delivers accurate results in various clinical scenarios (J. D. Lee & See, 2004; Rajpurkar et al., 2018). Reliability assures users that the AI system can be trusted to provide dependable recommendations, which is crucial in clinical environments where the stakes are high, and errors can have significant consequences (Glikson & Woolley, 2020; Siau & Wang, 2018).

2.3.2 Aligning AI Advice with Clinical Goals

Beyond perceived competence, transparency, and reliability, the alignment of AI advice with clinical goals is essential for building trust and encouraging reliance (Miller, 2019). AI systems that offer recommendations consistent with medical objectives reinforce the belief that they are valuable tools for achieving positive patient outcomes (Amann et al., 2020; Glikson & Woolley, 2020). In other words, AI systems that provide relevant and contextually appropriate advice are more likely to be trusted and used by healthcare providers. This alignment ensures that AI serves as a complementary tool to enhance clinical decision-making rather than conflicting with established medical practices (Reddy et al., 2019).

Effective communication and feedback mechanisms between AI systems and their users are also vital for fostering trust and reliance (Siau & Wang, 2018). Continuous interaction between healthcare providers and AI systems allows for real-time feedback, which helps refine the system's recommendations and ensures that they remain aligned with evolving clinical needs (Hoff & Bashir, 2015; Siau & Wang, 2018). AI systems that adapt based on user feedback and demonstrate responsiveness are perceived as more trustworthy and reliable, thereby increasing the likelihood of their advice being relied upon (J. D. Lee & See, 2004; Ribeiro et al., 2016).

Moreover, feedback loops in AI systems are essential for resolving any potential discrepancies between AI-generated advice and user expectations (Caruana et al., 2015). By refining its outputs based on user input, the AI system shows adaptability and responsiveness, further strengthening trust and reliance (Caruana et al., 2015; Wang et al., 2019). Therefore, the ability of AI systems to align their advice with clinical goals, coupled with transparent decision-making and effective communication, is key for determining the extent to which healthcare providers rely on AI-generated advice (Miotto et al., 2018; E. J. Topol, 2019).

Given the importance of reliance on AI advice, it is essential to explore the factors that shape trust and perceived competence in AI systems. These factors are fundamental to the adapted AIDUA model, which is discussed in the following section.

2.4 The Adapted AIDUA Model for AI Acceptance

The AIDUA model builds on the well-established frameworks of the TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating constructs specific to AI systems (Dwivedi et al., 2019). The TAM, originally developed by Davis (1989), explains that perceived usefulness and perceived ease of use are the key drivers of technology acceptance. TAM has been widely applied across various domains, demonstrating its robustness in predicting the adoption of new technologies (King & He, 2006; Marangunić & Granić, 2015). However, TAM primarily focuses on traditional technologies and does not fully address the complexities and unique challenges posed by AI systems (Venkatesh & Bala, 2008).

The UTAUT, proposed by Venkatesh et al. (2003), expanded on TAM by introducing additional constructs such as social influence, facilitating conditions, and performance expectancy. These constructs provide a more comprehensive understanding of technology adoption across different contexts, making UTAUT one of the most influential models in technology acceptance research (Venkatesh et al., 2012). Still, similar to TAM, UTAUT does not explicitly consider the specific characteristics of AI systems, such as their decision-making autonomy and their potential impact on user trust (Venkatesh et al., 2012).

The AIDUA model extends these frameworks to the AI domain by focusing on three critical factors—utilitarian motivation, interaction convenience, and task-technology fit—that influence the perceived competence of AI systems (Dwivedi et al., 2019). These factors are particularly relevant in the context of AI, where users must navigate the complexities of interacting with autonomous systems that process large amounts of data and provide recommendations with minimal human intervention (Dwivedi et al., 2019; Venkatesh & Bala, 2008). The perceived competence of AI systems is from importance, as it directly affects user trust and reliance on AI advice, ultimately determining the overall acceptance of AI.

The following sections analyze the impact of these factors on the perceived competence and acceptance of AI systems, with hypotheses embedded step by step within the relevant literature, all framed by the (adapted) AIDUA Model (Figure 1).

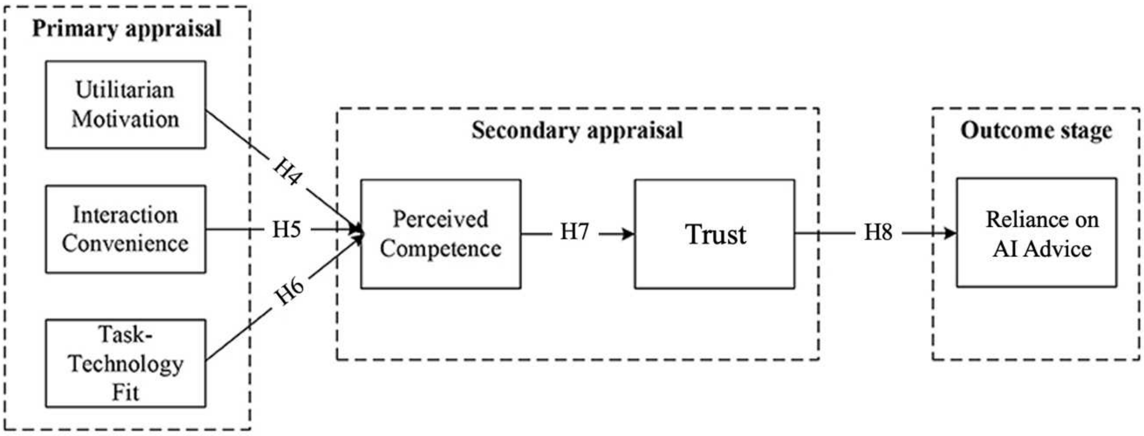

Figure 1: The adapted AIDUA Model

2.4.1 Utilitarian Motivation and Perceived Competence

Utilitarian motivation refers to the perceived usefulness and practical benefits that AI systems provide in healthcare, such as improving decision-making accuracy, enhancing efficiency, and reducing errors (Davis, 1989). In the context of AI acceptance, utilitarian motivation drives strong impact as a key predictor of perceived competence (Venkatesh et al., 2012). Healthcare professionals are more likely to perceive AI systems as competent when they recognize the significant practical benefits that these systems offer, such as improved diagnostic accuracy or optimized treatment plans (Secinaro et al., 2021). This perceived competence is essential for fostering trust in AI systems, which in turn influences their acceptance and reliance (Davenport & Kalakota, 2019; E. Topol, 2019).

The relationship between utilitarian motivation and perceived competence is particularly pronounced in high-stakes environments such as healthcare, where the consequences of incorrect decisions can be severe (Glikson & Woolley, 2020). For example, AI systems that consistently demonstrate their ability to provide accurate and reliable diagnoses are likely to be viewed as more competent, thereby enhancing user trust (Miotto et al., 2018). Consequently, utilitarian motivation serves as a foundational element in the AIDUA model, underscoring its importance in the overall acceptance of AI systems in healthcare. This leads to the following hypothesis:

Hypothesis H4: Utilitarian motivation is positively associated with perceived competence in AI giving healthcare advice.

2.4.2 Interaction Convenience and Perceived Competence

Interaction convenience refers to the ease with which users can interact with AI systems, encompassing factors such as the intuitiveness of the user interface, the clarity of system outputs, and the seamless integration of AI into existing clinical workflows (Venkatesh et al., 2003). In the healthcare context, the usability of AI technology is a critical determinant of its acceptance. AI systems that are user-friendly, offer clear and accessible outputs, and integrate smoothly into clinical workflows are more likely to be perceived as competent, which in turn enhances user trust and reliance (Holzinger, 2016).

The concept of interaction convenience is grounded in the broader human-computer interaction literature, which emphasizes the importance of usability and ease of use in technology adoption (Davis, 1989; Venkatesh & Bala, 2008). In healthcare, where time pressures and the need for accurate decision-making are paramount, AI systems that facilitate quick and easy interactions are particularly valued and AI systems that provide clear, concise, and actionable recommendations are more likely to be trusted and relied upon by healthcare professionals (Amann et al., 2020). Thus, interaction convenience not only affects the perceived competence of AI systems but also plays a crucial role in shaping the overall user experience, which is vital for the long-term acceptance and integration of AI in healthcare settings (Jiang et al., 2017). Given the critical role of interaction convenience in shaping user perceptions of AI competence, it is hypothesized that:

Hypothesis H5: Interaction convenience is positively associated with perceived competence in AI.

2.4.3 Task-Technology Fit and Perceived Competence

Task-technology fit refers to the degree to which an AI system supports the specific tasks it is designed to perform in a healthcare setting (Goodhue & Thompson, 1995). When AI systems align closely with the requirements of clinical tasks—such as diagnostics, patient monitoring, and treatment planning—they are perceived as more competent by healthcare professionals which makes task-technology fit a critical factor in influencing the perceived competence of AI systems (Venkatesh & Bala, 2008).

The concept of task-technology fit is based on the premise that technology is more likely to be adopted and perceived as effective when it is well-suited to the tasks it is intended to support (Goodhue & Thompson, 1995). In healthcare, this means that AI systems designed to assist with complex clinical tasks must provide relevant, accurate, and timely information that supports clinical decision-making (Rajkomar et al., 2019). For example, an AI system that accurately analyzes medical images and identifies potential issues that align with the clinician's expectations is likely to be viewed as more competent and reliable (Rajkomar et al., 2019). Therefore, a strong task-technology fit not only enhances the perceived effectiveness of AI systems but also bolsters healthcare professionals' confidence in their competence, which is crucial for fostering trust and reliance on AI-generated advice (Obermeyer & Emanuel, 2016; E. J. Topol, 2019). Given this important role of task-technology fit in shaping healthcare professionals' perceptions of AI systems, it is expected that systems well-aligned with clinical tasks will be perceived as more competent, which hypothesizes:

Hypothesis H6: Task-technology fit is positively associated with perceived competence in AI.

2.4.4 Perceived Competence, Trust, and Reliance on AI Advice

As stated, perceived competence is a primary driver of trust in AI systems, particularly in high-stakes environments such as healthcare, where the consequences of errors can be significant (Hoff & Bashir, 2015). Trust is essential for healthcare professionals to rely on AI-generated recommendations when making critical decisions (Siau & Wang, 2018). The relationship between perceived competence and trust is well-documented in the literature, with numerous studies indicating that when users perceive AI as highly competent, they are more likely to trust its recommendations, thereby increasing their reliance on the system (Dzindolet et al., 2003; J. D. Lee & See, 2004).

Trust serves as a mediator between perceived competence and reliance on AI advice. In other words, perceived competence directly influences trust, which in turn affects whether users choose to follow AI-generated advice. This mediation highlights the importance of perceived competence in the overall acceptance of AI systems (Hoff & Bashir, 2015; Liao et al., 2022). For instance, healthcare professionals are more likely to rely on AI systems that they perceive as competent in accurately diagnosing conditions or predicting patient outcomes (Miotto et al., 2018). The stronger the perceived competence of the AI system, the more likely it is that users will develop trust in the system and rely on its recommendations (Glikson & Woolley, 2020). This dynamic is crucial for the successful integration of AI into clinical practice, where trust and reliance on AI can significantly impact patient outcomes.

As seen, the interplay between perceived competence, trust, and reliance is foundational to the acceptance and effective use of AI in healthcare. As perceived competence influences trust, which in turn drives reliance on AI advice, the following hypotheses are proposed:

Hypothesis H7: Perceived competence in AI is positively associated with trust in the AI.
Hypothesis H8: Trust in AI is positively associated with reliance on AI advice.

2.5 The Impact of Anthropomorphic Features in AI Systems

Anthropomorphic features, such as human-like voices and appearances, make AI interactions more intuitive and engaging, which is crucial in healthcare settings (Go & Sundar, 2019). Human-like elements in AI interfaces can enhance user experience by making the technology feel more relatable and trustworthy (Epley et al., 2007; Go & Sundar, 2019). Research also shows that human-like avatars and natural language processing increase user engagement and trust, especially in scenarios where empathy and understanding are from importance (Waytz et al., 2014).

Studies indicate that users perceive anthropomorphic AI as more competent and trustworthy because these features convey empathy and understanding (Araujo, 2018). For example, chatbots with human-like attributes improve trust and satisfaction in patient interactions (Bickmore & Picard, 2005). However, these features can also introduce identity threats and increase effort expectancy, especially when users feel that the AI is too human-like, leading to discomfort (Jensen et al., 2021). This discomfort is often referred to as the "uncanny valley" effect, where AI that closely resembles humans but still falls short can evoke feelings of eeriness (Mathur & Reichling, 2016; Mori et al., 2012).

Moreover, initial interactions with anthropomorphic AI can influence trust in future encounters with similar technologies, even if those technologies lack anthropomorphic qualities (Waytz et al., 2014). This initial trust is crucial for long-term acceptance and reliance on AI in healthcare (Hancock et al., 2011). Understanding the balance between human-like and machine-like features in AI design is therefore essential for optimizing user trust and acceptance.

2.6 The Influence of AI Portrayals on User Acceptance

Research indicates that the portrayals of AI systems significantly influence user perceptions of utilitarian motivation, interaction convenience, and task-technology fit, all which impact perceived competence, trust, and reliance on AI advice. AI can be depicted in various forms—such as code-based, morph (a blend of human and machine features), or human-like—each influencing user perceptions in distinct ways (Araujo, 2018; Hancock et al., 2011).

AI systems portrayed as human-like or morph are generally perceived as more capable and relatable, which enhances utilitarian motivation and interaction convenience (Araujo, 2018; Hancock et al., 2011). However, the "uncanny valley" effect suggests that highly human-like AI may evoke discomfort or eeriness, potentially reducing these positive effects compared to morph portrayals (Glikson & Woolley, 2020; Mori et al., 2012). Conversely, AI portrayed as code-based might be perceived as less approachable and beneficial, resulting in lower utilitarian motivation and interaction convenience (Araujo, 2018).

Utilitarian motivation is a key factor in how users perceive the benefits of AI systems. When AI is portrayed as code-based, users may find it harder to perceive the practical benefits of the system due to its abstract and technical nature (Araujo, 2018). On the other hand, AI systems portrayed as morph or human-like are often seen as more relatable and beneficial, which can enhance utilitarian motivation (Luger & Sellen, 2016). However, the uncanny valley effect may lead to lower utilitarian motivation in human-like AI compared to morph portrayals, as the former can evoke discomfort if the AI appears too lifelike (Mori et al., 2012). Thus, the following hypotheses are formulated:

Hypothesis H1a: *AI portrayed as code-based will lead to lower levels of utilitarian motivation compared to AI portrayed as morph.*
Hypothesis H1b: *AI portrayed as code-based will lead to lower levels of utilitarian motivation compared to AI portrayed as human-like.*
Hypothesis H1c: *AI portrayed as human-like will lead to lower levels of utilitarian motivation compared to AI portrayed as morph.*

Interaction convenience is another critical factor influenced by AI portrayals. Human-like and morph AI systems are generally perceived as easier and more natural to interact with, which enhances interaction convenience (Araujo, 2018; Luger & Sellen, 2016). However, the uncanny valley effect may lead to decreased interaction convenience in human-like AI if users find the interaction unsettling (Mori et al., 2012). Morph AI, which balances human and machine characteristics, may offer higher interaction convenience without the discomfort associated with human-like AI (Glikson & Woolley, 2020). Thus, the following hypotheses are formulated:

Hypothesis H2a: *AI portrayed as code-based will lead to lower interaction convenience compared to AI portrayed as morph.*
Hypothesis H2b: *AI portrayed as code-based will lead to lower interaction convenience compared to AI portrayed as human-like.*
Hypothesis H2c: *AI portrayed as human-like will lead to lower interaction convenience compared to AI portrayed as morph.*

Task-technology fit is similarly affected by AI portrayals. AI portrayed as human-like may struggle with task-technology fit if users expect it to replicate human behavior but find that it falls short (Mathur & Reichling, 2016). In contrast, morph AI, which balances human and machine characteristics, may be seen as better suited for clinical tasks, leading to a stronger task-technology fit perception (Hancock et al., 2011). Thus, the following hypotheses are formulated:

Hypothesis H3a: *AI portrayed as code-based will lead to lower task-technology fit compared to AI portrayed as morph.*
Hypothesis H3b: *AI portrayed as code-based will lead to lower task-technology fit compared to AI portrayed as human-like.*
Hypothesis H3c: *AI portrayed as human-like will lead to lower task-technology fit compared to AI portrayed as morph.*

The integration of AI portrayals into the AIDUA model enhances our understanding of AI acceptance in healthcare. The full conceptual framework (Figure 2) incorporates AI portrayals as an antecedent variable influencing utilitarian motivation, interaction convenience, and task-technology fit, which in turn affect perceived competence, trust, and reliance on AI advice.

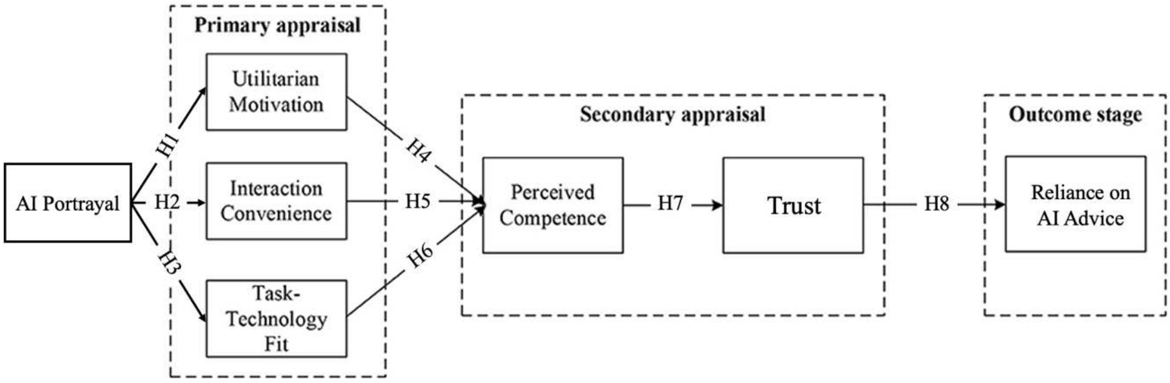

Figure 2: Full conceptual framework

To test these fourteen hypotheses, a study was conducted, the methodological approach and results of which will be described in the following chapters. The integration of AI portrayals variables into the AIDUA model provides a comprehensive framework for understanding AI acceptance in healthcare, guiding both theoretical exploration and practical application.

3 Methodology

3.1 Research Design

The objective of the conducted study is to examine the causal effect of receiving healthcare advice from different portrayals of AI (code-based vs. morphed vs. human-like) on following AI advice. Thus, an experimental study has been implemented, as this represents a suitable approach for examining causality within hypothetical scenarios (Malhotra & Ramalingam, 2023). This setup allows to explore causal relationships between the portrayals of AI and subsequent user responses within a controlled experimental environment, thereby aiming to enhance internal validity, while addressing specific hypotheses derived from the AIDUA model. To still ensure a high level of external validity, the scenarios were created as realistic as possible and taken from a real-life context.

A quantitative approach was used to answer the research questions about the different AI portrayals and their effects on the recipients' perception. For the implementation and to ensure a random assignment of participants to the different scenarios the online tool Qualtrics was employed (Weber, 2021). A between-subjects design was employed to examine the behavior of participants across the three conditions (AI code-based, AI morph, AI human-like) while preventing spillover effects (Charness et al., 2012). To provide additional clarification in the causal impact, predictors in three different levels were included: utilitarian motivation, interaction convenience, and task-technology fit in the first level, perceived competence in the second level and trust as a third level mediator. These variables contribute to the finalization of the research model, ending up being a serial mediation model and an adaptation of the AIDUA model.

With the research design established, the next step involved developing and implementing a survey that accurately captures the variables of interest.

3.2 Survey Development and implementation

Algorithms already support people in making better and less biased decisions across various fields (Lai & Tan, 2019; Venkatesh et al., 2012). This study aimed to replicate a realistic scenario where a patient must decide on immediate appendicitis surgery due to intense abdominal pain. Participants were asked to make this high-risk medical decision to test the conceptual model and its hypotheses.

To provide a scholarly foundation and test the reliance on AI advice, the Artificially Intelligent Device Use Acceptance (AIDUA) Model was adapted. This adaptation ensured accurate measurement of utilitarian motivation, interaction convenience, and task-technology fit, which influence perceived competence, subsequently impacting trust and reliance on AI advice.

Questions were tailored for clarity and context-specificity.

The survey included scales, based on the literature introduced in Chapter 2, to measure the following constructs:

- Utilitarian motivation (UM): Practical benefits and usefulness of AI.
- Interaction convenience (IC): Ease and comfort of AI interaction.
- Task-technology fit (TTM): Alignment of AI with required tasks.
- Perceived competence (PC): AI's capability and reliability.
- Trust: Confidence in AI's recommendations.
- Reliance on AI Advice: Willingness to follow AI advice.

Following the creation of the survey, attention will be focused on the sampling process and the procedures used to collect data from participants.

3.3 Sample and Procedure

Data was acquired using a nonprobability sample technique; with volunteer participants recruited through social media (Naresh et al., 2017), as well as through the platforms surveycycle.com and surveyswap.io, where researchers can participate in surveys in exchange for own respondents for their survey. No exclusion criteria were applied, aiming to include a broad and diverse participant pool.

Participants in the survey were initially greeted with an informed consent section, where they were thanked for their participation and briefed about the survey's structure and the voluntary nature of their involvement. The survey consisted of a high-risk medical decision-making scenario related to receiving health advice. To test the different reliance on AI advice in isolation, the survey was split at one point and one of three scenarios was presented to the participant with a picture and the referring descriptive text for either AI code-based, AI morph, or AI human-like. Under all conditions, respondents received identical advice, allowing to control for the quality of advice. Responses were collected on a Likert scale from 0 to 100. Previously, the word AI was defined (Alowais et al., 2023), to prevent a possible influence of the trust component independently of the manipulation because of possible lack of knowledge of the participants. In the end, the survey concluded with demographic questions to gather insights into the background of the respondents. The survey was designed to take approximately 3 minutes.

Between April 28th and July 14th, a total of 278 valid survey answers were collected (55.0% female, 43.9% male, 0.7% non-binary/ third gender and 0.4% prefer not to say). Beforehand, all answers of participants who failed one of the attention checks were excluded. Their age ranged from 18 to 73 years (M = 30.97, SD = 10.373) and most of the respondents had a Bachelor’s degree (N = 125) followed by participants holding a Master’s degree (N = 92). Furthermore, most respondents were either employed at the time of the survey (N = 145) followed by people currently studying (N = 95). While the distribution of the survey on online platforms attracted a wide range of nationalities, most participants were of European nationality (N = 257). Most participants rated themselves as being not at all familiar with AI (N = 74). For more details on the demographic statistics, see Appendix A.

The survey questions were presented in a randomized order, and to independently test the three different AI portrayals (AI code-based, AI morph, and AI human-like), the participants were randomly assigned to corresponding distinct groups to ensure the validity and reliability of the results. For the following statistical tests and analyses, I have excluded the "non-binary/third gender" group (N = 2) and the "prefer not to say" group (N = 1), given the low number, as I use these as control variables. After data cleaning, there were N = 90 participants in the AI code-based group, N = 96 participants in the AI morph group, and N = 89 participants in the AI human-like group.

After detailing the sample and data collection process, it is essential to explain how the key variables in this study were measured.

3.4 Variable Measurement

3.4.1 Independent Variable

AI portrayals: The independent variable AI portrayals represent the different ways AI is presented to the participants. This study categorizes AI portrayals into three distinct types: code-based, morph, and human-like. Participants were presented with scenarios that included a picture of each AI portrayals along with identical advice. This approach ensured that any differences in participant responses could be attributed to the influence of the source rather than the accuracy of the advice (Glikson & Woolley, 2020).

3.4.2 Dependent Variable

Reliance on advice: The dependent variable measured patient reliance on AI advice. This was assessed by evaluating how much weight participants assigned to the advice from the different AI portrayals. The Judge-Advisor System (JAS) paradigm was employed, which involves participants making an initial decision under uncertainty, receiving advice, and then making a second, potentially revised decision (Sniezek & Buckley, 1995). This method effectively captures the extent to which participants rely on the advice provided by the AI. The difference between the first answer and the second answer, divided by the difference between the first answer and the advice, represents the dependent variable, the Weight on Advice (WOA). This approach aligns with strategies for revising judgments as discussed by Soll & Larrick (2009), who explored how individuals incorporate others' opinions into their decision-making processes.

3.4.3 Predictors

Utilitarian motivation: This was measured by assessing the perceived practical benefits and usefulness of the AI system. Questions were designed to capture the extent to which participants found the AI helpful in enhancing decision-making processes. One example item reads "Using this kind of AI for giving health advice in this case is effective." (*1 = Strongly disagree; 7 = Strongly agree*). All four items were measured using a seven-point Likert scale, which allowed participants the option to remain neutral between the two descriptors. The scale was adapted from Davis (1989) and Venkatesh & Davis (2000), who developed and validated similar items for measuring perceived usefulness in technology acceptance.

Interaction convenience: This variable was assessed by evaluating the ease and comfort with which participants could interact with the AI systems. Questions focused on the user-friendliness and intuitiveness of the AI interfaces. One example item reads "This AI system can be used at any time for recommendations." (*1 = Strongly disagree; 7 = Strongly agree*). All four items were measured using a seven-point Likert scale, which allowed participants the option to remain neutral between the two descriptors. This scale was adapted from measures of ease of use, originally developed by Davis (1989).

Task-technology fit: This was measured by examining how well the AI technology supported the specific tasks it was designed to perform. Participants rated the alignment between the AI's capabilities and the requirements of the medical decision-making tasks. One example item reads "In helping the doctor to decide for the medical practice, the AI system was very helpful." (*1 = Strongly disagree; 7 = Strongly agree*). All four items were measured using a seven-point Likert scale, which allowed participants the option to remain neutral between the two descriptors. This scale draws on the Task-Technology Fit (TTF) model developed by Goodhue & Thompson (1995).

Perceived Competence: Participants' beliefs about the capability and reliability of the AI were measured to assess perceived competence. This included questions about the AI's accuracy in diagnostics and recommendations. The scale was adapted from previous work by Parasuraman et al. (2000) on the perceived competence of automated systems.

Trust: Trust was measured using a combination of items adapted from Jamaludin & Ahmad (2013) and Gold et al. (2015). These items assessed participants' confidence in the AI's recommendations and their overall trust in the AI system's reliability.

3.4.4 Control variables

To accurately isolate the effects of the independent on the dependent variables and to ensure reliable and valid conclusion, the study in controlling for gender and AI familiarity.

Gender: This variable is controlled for because prior research has demonstrated that men and women may respond differently to technology, including AI systems. Studies have found that gender can influence attitudes towards technology adoption, trust in AI, and decision-making processes. For example, research by Venkatesh & Morris (2000) suggests that gender differences exist in the perceived usefulness and ease of use of technology, which can impact technology acceptance and interaction.

AI familiarity: This variable is controlled for because participants with more experience or knowledge of AI might exhibit different levels of trust, perceived usefulness, or reliance on AI advice compared to those who are less familiar with the technology. Previous studies, such as those by Mcknight et al. (2011), have shown that prior experience with technology can affect trust and reliance on AI, potentially skewing the results if not accounted for.

Having defined the measurement of variables, the reliability of these scales and the interrelationships between them were thoroughly evaluated.

3.5 Scale Reliability and intercorrelations

Although the scales used in this experiment have proved reliable in past studies (Dzindolet et al., 2003), a reliability analysis was conducted to test for Cronbach's alpha (α). Reliability refers to the internal consistency of the constructs used in the study. A construct is deemed reliable if it has an α value greater than 0.70 (Gliem & Gliem, 2003).

The reliability analysis results demonstrate that the scales used in the study are dependable and consistent. The utilitarian motivation scale achieved a high Cronbach's alpha of .912, indicating excellent internal consistency. Similarly, the interaction convenience scale (α = .827) and task technology fit scale (α = .837) both showed strong reliability. The trust scale also performed well, with an alpha of .878, while the perceived confidence scale, with an alpha of .796, still meets the threshold for acceptable reliability. These findings confirm the robustness of these scales in accurately measuring their respective constructs.

The intercorrelation matrix shows the relationships between the variables used in the study. Several significant correlations were observed. For instance, there is a moderate positive correlation between trust and utilitarian motivation (r = .741, p < .001), indicating that participants who perceive the AI as more useful also tend to trust it more. Similarly, task-technology fit is strongly correlated with interaction convenience (r = .666, p < .001), suggesting that AI systems that are easy to interact with are also perceived as well-suited to the tasks at hand.

On the other hand, age showed weak and mostly non-significant correlations with many variables, such as AI familiarity (r = -.113, p = .060), indicating that these demographic factors had minimal impact on participants' perceptions of the AI. Notably, however, reliance on advice was significantly correlated with AI familiarity (r = .201, p = .001), suggesting that participants with more familiarity with AI were more likely to rely on the advice provided by the AI systems.

These intercorrelations, as seen in Table 1, highlight the complex relationships between the predictors, the dependent variable, and the control variables, providing insights into how various factors influence reliance on AI advice in this study.

		Age	Gender	AI familiar	UM	IC	TTF	Trust	PC	Reliance
Age	Pearson Correlation	--								
	N	278								
Gender	Pearson Correlation	0,002	--							
	Sig. (2-tailed)	0,979								
	N	275	275							
AI familiar	Pearson Correlation	-0,113	0,262**	--						
	Sig. (2-tailed)	0,060	0,000							
	N	278	275	278						
UM	Pearson Correlation	-0,071	0,274**	0,269**	--					
	Sig. (2-tailed)	0,240	0,000	0,000						
	N	278	275	278	278					
IC	Pearson Correlation	0,003	0,176**	0,191**	0,686**	--				
	Sig. (2-tailed)	0,957	0,003	0,001	0,000					
	N	278	275	278	278	278				
TTF	Pearson Correlation	-0,050	0,252**	0,264**	0,760**	0,666**	--			
	Sig. (2-tailed)	0,403	0,000	0,000	0,000	0,000				
	N	278	275	278	278	278	278			
Trust	Pearson Correlation	-0,045	0,310**	0,349**	0,741**	0,551**	0,705**	--		
	Sig. (2-tailed)	0,455	0,000	0,000	0,000	0,000	0,000			
	N	278	275	278	278	278	278	278		
PC	Pearson Correlation	-0,106	0,238**	0,349**	0,685**	0,558**	0,626**	0,705**	--	
	Sig. (2-tailed)	0,078	0,000	0,000	0,000	0,000	0,000	0,000		
	N	278	275	278	278	278	278	278	278	
Reliance	Pearson Correlation	-0,003	0,201**	0,136*	0,442**	0,350**	0,369**	0,463**	0,357**	--
	Sig. (2-tailed)	0,967	0,001	0,023	0,000	0,000	0,000	0,000	0,000	
	N	278	275	278	278	278	278	278	278	278

** Corellation is significant at the 0.01 level (2-tailed).

* Corellation is significant at the 0.05 level (2-tailed).

Table 1: Intercorrelation Matrix

With reliable measures and established intercorrelations, the next phase involved testing the hypotheses to explore the effects of AI portrayals on participant responses.

3.6 Hypotheses testing

Starting with the control variables, gender (UM: ($F(1, 270) = 12.528$, $p < .001$) IC: ($F(1, 270) = 4.343$, $p = .038$) TTF: ($F(1, 270) = 10.170$, $p = .002$) and familiarity with AI (UM: ($F(1, 270) = 14.540$, $p < .001$) IC: ($F(1, 270) = 7.009$, $p = .009$) TTF: ($F(1, 270) = 13.428$, $p < .001$) were used as control variables, while age was excluded due to its lack of significant correlation with the latent variables.

Regarding the impact of AI portrayals (code-based, morph, and human-like) on utilitarian motivation (**H1a, H1b, H1c**), interaction convenience (**H2a, H2b, H2c**), and task-technology fit (**H3a, H3b, H3c**), a Multivariate Analysis of Variance (MANOVA), was conducted by using the IBM SPSS software. Given the presence of three distinct groups based on AI portrayals, the MANOVA approach was selected to analyze the variance across these groups. The results indicated that the portrayals of AI (whether as code-based, morph, or human-like) did not significantly affect any of the three dependent variables. Specifically, no significant differences were found between the AI portrayals for utilitarian motivation ($F(2, 270) = .506$, $p = .603$), interaction convenience ($F(2, 270) = .566$, $p = .569$), or task-technology fit ($F(2, 270) = 1.003$, $p = .368$). Based on these non-significant results, further pairwise comparisons are unnecessary. This outcome suggests that the variations in AI portrayals were not substantial enough to influence participants' perceptions across these dimensions, thereby leading to the rejection of hypotheses **H1a, H1b, H1c, H2a, H2b, H2c, H3a, H3b,** and **H3c**.

Subsequent univariate Analysis of Variance (ANOVAs) confirmed these findings, with none of the individual analyses yielding significant results. The results indicate that participants' utilitarian motivation, interaction convenience, and task-technology fit were consistent across the different AI portrayals, supporting the notion that the portrayals did not create sufficiently distinct experiences to impact these factors. For more details, see Appendix B.

To test hypotheses **H4** through **H6**, a multiple hierarchical regression analysis was conducted. The regression model assessed the impact of utilitarian motivation, task-technology fit, and interaction convenience on perceived competence in AI. From the covariates, gender ($\beta = .011$, $p = .811$) did not have a significant impact in the analysis, while AI familiarity ($\beta = .176$, $p < .001$) had a significant impact.

The first step of the regression, which included AI familiarity and gender, accounted for 15.6% of the variance in perceived competence ($R^2 = .156$, $F(2, 272) = 25.218$, $p < .001$). When UM, TTF, and IC were added to the model in the second step, the explained variance increased significantly to 53.7% ($R^2 = .537$, $F(5, 269) = 62.303$, $p < .001$).

Among the predictors, utilitarian motivation had the strongest effect on perceived competence, serving as the most suitable predictor ($\beta = .417$, $p < .001$). task-technology fit followed as the next strongest predictor ($\beta = .195$, $p < .001$), and interaction convenience had the least effect ($\beta = .104$, $p = .043$). AI familiarity also contributed significantly to the model, further enhancing the understanding of perceived competence in AI.

Given that the hypotheses are two-sided, all p-values were divided by two, except for AI familiarity. These findings support hypotheses **H4, H5,** and **H6**, with utilitarian motivation showing the most substantial influence on perceived competence in AI, followed by task-technology fit and interaction convenience. For more details, see Appendix C.

To test **H7**, a multiple hierarchical regression was conducted to examine the effect of perceived competence on trust in AI, using gender and AI familiarity as control variables. The initial model, which included the control variables, explained R^2 =0.177 of the variance in trust ($F(2, 272) = 29.320$, $p < .001$). Gender was found to be a significant predictor β=1.33, p = .002, while AI familiarity was not significant $\beta = .083$ $p = .069$. Upon adding perceived competence, the model's explanatory power increased significantly to $R^2 = .534$, $F(2, 271) = 103.644$, $p < .001$. Perceived competence was a strong predictor of trust β =0.650, p <.001, confirming **H7**. For more details, see Appendix D.

To test **H8**, also a hierarchical regression was performed to investigate the impact of trust on reliance on AI advice, with the same control variables. The initial model accounted for R^2 = .047 of the variance in reliance ($F(2, 272) = 6.724$, $p = .001$), with neither gender ($\beta = .071$, $p = .217$) nor AI familiarity ($\beta = -.053$, $p > .362$ being significant predictors. When trust was added, the model's R^2 increased to $R^2 = .226$ ($F(3,271)$= 26.363 , $p < .001$). Trust was a significant predictor of reliance $\beta = .466$, $p < .001$, though the effect size was smaller than that of perceived competence on trust, confirming **H8**. For more details, see Appendix E.

A paired samples t-test was conducted to compare the means before and after the advice intervention. The results revealed a significant difference in the scores for the pre-advice (M = 55.874, SD = 28.772) and post-advice (M = 59.385, SD = 29.945) conditions; $t(277) = -2.391$, $p = .017$. This suggests that the weight on advice (WOA) increased following the intervention.

A mixed ANOVA was conducted to examine the differences between advice measurements as within factor and between groups as between factor. The means and standard deviations for each group before and after the intervention were as follows:

	Advice	***M***	***SD***
Group 1	Pre-advice	62.363	28.335
(AI code-based)	Post-advice	65.725	28.693
Group 2	Pre-advice	50.698	29.259
(AI morph)	Post-advice	54.396	30.868
Group 3	Pre-advice	54.846	27.733
(AI human-like)	Post-advice	58.308	29.366

Table 2: Means and Standard Deviations of each group

The F-test for the main effect of advice was significant, $F(1, 275) = 5.660$, $p = .018$, indicating that the WOA was significantly affected by the advice intervention across all groups. The F-test for the main effect of AI portrayals was also significant, $F(2, 275) = 4.55$, $p = .011$, suggesting that the type of AI portrayals influenced WOA. However, the interaction effect of advice and AI portrayals was not significant, $F(2, 275) = .005$, $p = .995$, indicating that the increase in WOA following the advice intervention did not differ significantly across the different AI portrayals. For more details on the WOA, see Appendix F.

Having established a robust methodological framework, the following section presents the results of the study, providing detailed insights into the impact of AI portrayals on participants' reliance on AI advice.

4 Discussion

4.1 Research findings

This study set out to investigate the impact of different AI portrayals—code-based, morph, and human-like—on participants' reliance on AI advice within a healthcare decision-making context. The primary research question asked whether the visual and conceptual portrayals of AI would significantly influence users' perceptions and their subsequent reliance on AI advice.

The results revealed that the portrayals of AI did not significantly affect Utilitarian Motivation, Interaction Convenience, or Task-Technology Fit, leading to the rejection of hypotheses **H1a, H1b, H1c, H2a, H2b, H2c, H3a, H3b,** and **H3c**. These findings suggest that, contrary to the initial hypotheses, the superficial differences in AI representation did not substantially alter participants' perceptions of the AI's usefulness, ease of interaction, or fit for the task at hand (Logg et al., 2019).

The lack of significance across **H1** through **H3** suggests that the portrayals tested were not sufficiently differentiated in participants' perceptions, aligning with the overall non-significant findings.

Conversely, strong support was found for hypotheses **H4, H5,** and **H6**, which posited that Utilitarian Motivation, Task-Technology Fit, and Interaction Convenience would significantly predict perceived competence in AI. Utilitarian Motivation emerged as the most influential factor, emphasizing the importance of perceived usefulness in shaping how competent users believe the AI to be (Davis, 1989). Additionally, hypotheses **H7** and **H8** were confirmed, as perceived competence was shown to be a critical driver of trust in AI, which in turn led to higher reliance on AI advice (Madhavan & Wiegmann, 2007; Mayer et al., 1995).

These findings provide important insights into the factors that influence user reliance on AI and suggest areas for further investigation. The next section discusses the theoretical implications of these results in more detail.

4.2 Theoretical Implications

The findings of this study significantly contribute to the theoretical understanding of AI adoption, particularly in healthcare, by reinforcing and refining models like the Artificially Intelligent Device Use Acceptance (AIDUA) model and the Technology Acceptance Model (TAM). The results challenge certain assumptions in the literature while offering insights that can enhance AI acceptance models.

This study confirms the AIDUA model's emphasis on utilitarian motivation, interaction convenience, and task-technology fit as key predictors of perceived competence, which in turn influences trust and reliance on AI (Davis, 1989; Dwivedi et al., 2019; Venkatesh & Davis, 2000). The strong relationship between utilitarian motivation and perceived competence supports the TAM's focus on perceived usefulness as a critical determinant of technology acceptance, suggesting that users are more likely to trust AI when they perceive it as practically beneficial and effective in enhancing decision-making processes (Secinaro et al., 2021; E. J. Topol, 2019). This finding aligns with the broader literature on technology acceptance, which consistently highlights the importance of perceived usefulness in driving user engagement with new technologies (King & He, 2006; Venkatesh et al., 2012).

Additionally, this study's adaptation and extension of the AIDUA model to include visual portrayals of AI—whether code-based, morph, or human-like—revealed that these factors do not significantly impact perceptions of utility, convenience, or task fit. These findings challenge the notion that anthropomorphic features or visual representations significantly alter user perceptions of AI, a concept widely discussed in the literature (Epley et al., 2007; Glikson & Woolley, 2020). Instead, the study suggests that deeper functional aspects, such as competence and reliability, are more critical in driving user acceptance, echoing findings from Hoff & Bashir (2015) that emphasize the importance of trustworthiness over appearance in automation. This insight is particularly relevant in high-stakes environments like healthcare, where accuracy and reliability are essential (Mittelstadt, 2019; Rajkomar et al., 2019).

The study further challenges assumptions that human-like features in AI inherently enhance trust and engagement (Hancock et al., 2011; Waytz et al., 2014). While previous research suggests human-like AI can improve user trust and interaction satisfaction, this study demonstrates that these effects do not significantly extend to perceptions of AI competence or its practical benefits in a healthcare setting. This divergence from the literature suggests that while anthropomorphic features may enhance initial user engagement, they do not necessarily influence deeper cognitive evaluations related to AI's functionality. This is supported by research indicating that users in critical settings often prioritize performance and reliability over human-like characteristics (J. D. Lee & See, 2004; Madhavan & Wiegmann, 2007). Therefore, the study advocates for a more nuanced approach in designing AI systems, focusing on improving the AI's functional capabilities rather than solely enhancing its visual or human-like features.

Trust in AI is a crucial factor in the adoption of automated systems, as extensively studied in the literature (Hoff & Bashir, 2015; J. D. Lee & See, 2004; Madhavan & Wiegmann, 2007). This study confirms the significant role of perceived competence in fostering trust, which subsequently leads to higher reliance on AI advice, consistent with the AIDUA model and the broader literature on technology acceptance (Mayer et al., 1995; Siau & Wang, 2018). The findings suggest that perceived competence acts as a mediator between utilitarian motivation, task-technology fit, and trust in AI, aligning with frameworks proposed by researchers like Hoff & Bashir (2015). This mediation effect underscores the importance of ensuring that AI systems are not only functionally effective but also perceived as such by users, which is critical for building trust in these systems (Mcknight et al., 2011). Furthermore, the significant relationship between trust and reliance on AI advice reinforces the idea that trust is a key determinant of user behavior in high-risk decision-making contexts, particularly in healthcare, where the stakes are high (Mittelstadt, 2019; E. Topol, 2019).

The broader theoretical implications of these findings suggest a shift in how AI adoption models are conceptualized, particularly in high-stakes fields like healthcare (Goodhue & Thompson, 1995). The results highlight the need for models that prioritize functional competence and trustworthiness over visual or superficial elements, aligning with the growing emphasis on practical utility and reliability in AI systems (Miotto et al., 2018; E. Topol, 2019). This study also underscores the importance of integrating user-centered design principles into AI development, ensuring that AI systems are not only technically proficient but also perceived as such by end-users. This approach aligns with the principles of human-computer interaction and suggests that the future of AI adoption research should focus more on how users perceive and interact with AI's functional capabilities rather than its visual design (Holzinger, 2016; Venkatesh & Bala, 2008).

4.3 Managerial Implications

In addition to the theoretical contributions, the insights gained from this study have significant implications for managers and practitioners involved in the design and implementation of AI systems, particularly within the healthcare domain. The findings suggest that perceived competence and trust are the most critical factors influencing reliance on AI.

To foster trust and ensure that AI systems are perceived as competent, the development of AI systems should emphasize accuracy and reliability, achieved by investing in advanced machine learning algorithms and ensuring that these systems undergo rigorous testing before deployment (E. Topol, 2019). AI systems in healthcare must meet the high standards expected in such settings, where the stakes are often life-or-death (Secinaro et al., 2021; E. Topol, 2019). Transparency in AI systems is equally crucial. Managers should ensure that AI systems provide clear and understandable explanations for their recommendations, offering insights into how decisions are made and what data is used. This approach can help demystify the AI's decision-making process and make users feel more comfortable relying on its outputs (Siau & Wang, 2018). Integrating explainable AI (XAI) techniques, which allow users to see and understand the logic behind AI decisions, can enhance transparency and trust (Gunning et al., 2019).

While visual and anthropomorphic elements can enhance initial user engagement, these features should not be the primary focus. The study suggests that functionality and trustworthiness should take precedence. Users in high-stakes environments like healthcare prioritize systems that are not only visually appealing but, more importantly, perform effectively and reliably (Mittelstadt, 2019; Rajkomar et al., 2019). This suggests that while it is important to design AI systems that are user-friendly and aesthetically pleasing, these efforts should be balanced with investments in the practical utility of the system. For example, AI interfaces should be designed to be intuitive and easy to navigate, but the underlying technology must also be robust enough to deliver consistent and accurate results (Glikson & Woolley, 2020).

Managers should also consider how AI systems can be seamlessly integrated into existing clinical workflows. AI tools that align well with the tasks they are intended to support—known as task-technology fit—are more likely to be accepted and trusted by users (Goodhue & Thompson, 1995). This involves designing AI systems that complement, rather than disrupt, the work of healthcare professionals, ensuring that the technology enhances rather than complicates their tasks. To achieve this, it is essential to involve end-users—such as doctors, nurses, and other healthcare staff—in the design and implementation process. By understanding their needs and pain points, AI systems can be tailored to better fit the clinical environment, increasing the likelihood of successful adoption (Venkatesh et al., 2012).

In addition to technical and design considerations, managers must address the ethical and regulatory aspects of AI implementation. As AI systems increasingly influence critical decisions in healthcare, ensuring that these systems operate within ethical guidelines and comply with relevant regulations is vital. This includes ensuring data privacy, preventing biases in AI decision-making, and maintaining accountability for AI-driven decisions (AI HLEG, 2019; Mittelstadt, 2019). The European Union has emphasized the importance of Trustworthy Artificial Intelligence (TAI), as outlined by the European Commission's High-Level Expert Group on AI (AI HLEG), which provides a framework for developing AI systems that prioritize ethical considerations such as transparency, accountability, and fairness (AI HLEG, 2019; Kaur et al., 2022). Certification processes, as highlighted by Cihon et al. (2021), are essential in communicating trustworthiness, particularly to end-users, and are emerging as a key regulatory focus in the EU's efforts to build trust in AI systems.

Managers should work closely with legal and ethical experts to develop AI systems that not only perform well but also align with ethical standards and regulations. This proactive approach can help mitigate risks and build confidence among users, further supporting the adoption of AI technologies (AI HLEG, 2019; Thiebes et al., 2021).

Additionally, it is of importance for organizations to recognize that the implementation of AI is an ongoing process. As AI technologies evolve, so too will user expectations and regulatory requirements. Managers should establish mechanisms for continuous monitoring and improvement of AI systems, ensuring that they remain relevant, effective, and trusted over time. This could involve regularly updating the AI's algorithms based on new data, incorporating user feedback into system improvements, and staying informed about the latest developments in AI ethics and regulation (Campos Zabala, 2023; Cath et al., 2016). By adopting a mindset of continuous improvement, organizations can ensure that their AI systems continue to meet the needs of users and maintain their trust in the long term.

By focusing on building competence and trust, balancing functionality with aesthetics, ensuring seamless integration into workflows, addressing ethical considerations, and committing to continuous improvement, managers can significantly enhance the successful adoption and utilization of AI systems in healthcare and other critical domains.

4.4 Limitations and future research

While this study provides valuable insights, it is important to acknowledge its limitations, which offer directions for future research. One limitation is the use of static images to represent AI portrayals, which may have constrained the ability to observe subtle effects on user perceptions. Previous research indicates that dynamic representations, such as videos or interactive simulations, can elicit stronger emotional and cognitive responses, potentially leading to different user behaviors (Nass & Moon, 2000; Reeves & Nass, 1996). Future studies could explore these more immersive formats to assess whether they reveal significant differences in how users respond to various AI portrayals.

The study's sample, while diverse, was not globally representative, which may limit the generalizability of the findings, as cultural and regional factors can significantly influence perceptions of technology (Hofstede, 2001). Expanding future research to include a more varied and globally representative participant pool could help determine whether these factors play a critical role in shaping user trust and reliance on AI.

Moreover, the study was conducted within the context of healthcare decision-making, which, while critical, is just one of many domains where AI is increasingly applied. The decision-making context may significantly influence how users perceive and rely on AI systems (Dietvorst et al., 2015). Future research should investigate AI adoption in different contexts, such as financial advising, legal decision-making, or customer service, to provide a more comprehensive understanding of how AI portrayals and functionality impact user behavior across various domains.

While this study focused on perceived competence and trust as key factors influencing AI reliance, it did not extensively explore other potentially important factors such as emotional responses, social influence, or the role of familiarity with AI technology. These elements have been highlighted in the literature as significant drivers of technology adoption and user behavior (Gefen et al., 2003). Future studies could delve deeper into these aspects to provide a more holistic view of the mechanisms driving AI adoption.

The study suggests that users may prioritize functional competence and trustworthiness over superficial aspects of AI portrayals, but it remains possible that certain user segments or specific contexts could exhibit different preferences. Mayer et al.'s (1995) model of trust supports the notion that functional aspects are paramount, but additional research is needed to confirm whether this holds true across all user groups and scenarios. Addressing these limitations and expanding the scope of future research will be essential to advancing our knowledge. By exploring more diverse contexts, employing dynamic representations, and considering additional psychological and social factors, future research can enhance the design and implementation of AI systems, ensuring they are more effectively tailored to meet the needs of various user populations.

5 Conclusion

This thesis has explored the intricate relationship between AI portrayals, perceived competence, trust, and user reliance on AI in a healthcare setting. The study revealed that while the visual characteristics of AI, such as whether it is presented as code-based, morph, or human-like, may have a limited impact on user perceptions, it is the AI's perceived competence and the trust it engenders that ultimately determine whether users will rely on its advice. These findings underscore the importance of developing AI systems that are not only technologically advanced but also capable of building and maintaining user trust.

As AI continues to be integrated into critical decision-making processes, particularly in sensitive domains like healthcare, understanding the factors that drive user acceptance and reliance becomes increasingly vital. The insights gained from this research offer a valuable foundation for designing AI systems that can effectively support and enhance human decision-making. By focusing on competence and trustworthiness, we can ensure that AI systems are not only tools for efficiency but also trusted partners in delivering better outcomes in healthcare and beyond.

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Appendix

Appendix 1: Survey

Start of Block: Informed Consent

Welcome and thank you for participating in this survey as part of my Master's Thesis at Católica Lisbon School of Business and Economics. This study consists of a decision scenario and multiple questions related to it.

Your participation in this survey is entirely voluntary and you may withdraw anytime. All responses will be kept confidential and used for academic purposes only. The survey should take approximately 3 minutes to complete. If you have any questions or require further information about the study, please contact me at s-tpfrunder@ucp.pt (Teresa Pfründer).

By proceeding with the survey, you acknowledge that you have read and understood this consent form and agree to participate in the research. Thank you for your valuable contribution!

End of Block: Informed Consent

Start of Block: Section 1 - Scenario Presentation

In the following section, you will be presented with a scenario involving receiving health advice. Please read the following scenario carefully and answer the questions that follow based on your perceptions. Your honest responses are invaluable to my research.

Page Break

Imagine you're in the emergency room due to intense abdominal pain. A doctor assesses your symptoms and suggests it might be appendicitis. The doctor isn't a specialist in this area but recommends immediate surgery based on general medical guidance. You're sent to the surgery ward for the operation. You wonder whether it is perhaps better to gather a second opinion before being operated on.

Q1 Based on the doctor's recommendation, how likely would you be to follow this advice and have the procedure done?

Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

	0 10 20 30 40 50 60 70 80 90 100
Me following the doctor's advice is ... ()	

Page Break

End of Block: Section 1 - Scenario Presentation

Start of Block: Section 2a Group 1: AI Code

Now, for you to be able to understand the following scenario completely, here is a short definition of Artificial Intelligence:
"Artificial Intelligence (AI) is a rapidly evolving field of computer science that aims to create machines that can perform tasks that typically require human intelligence." (Revolutionizing Healthcare: The Role of Artificial Intelligence in Clinical Practice, 2023)

In the surgery ward, the doctor now consults an AI system for a second opinion. This AI system has no physical existence, it is merely code, as you can see below. The AI, through complex algorithms, confirms the risk of appendicitis and suggests immediate surgery.

Q2a Now, having received the AI system's assessment, how likely would you be to follow this advice and undergo the procedure?

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

0 10 20 30 40 50 60 70 80 90 100

Me following the doctor's advice is ... ()	

Page Break

Q3a Please state your agreement with the following attributes regarding the AI Code's recommendation:
The AI system is ...

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
... intelligent. (1)	○	○	○	○	○	○	○
... skillful. (2)	○	○	○	○	○	○	○
... capable. (3)	○	○	○	○	○	○	○
... effective. (4)	○	○	○	○	○	○	○

Q4a Please state your agreement with the following statements regarding the AI system's recommendation:

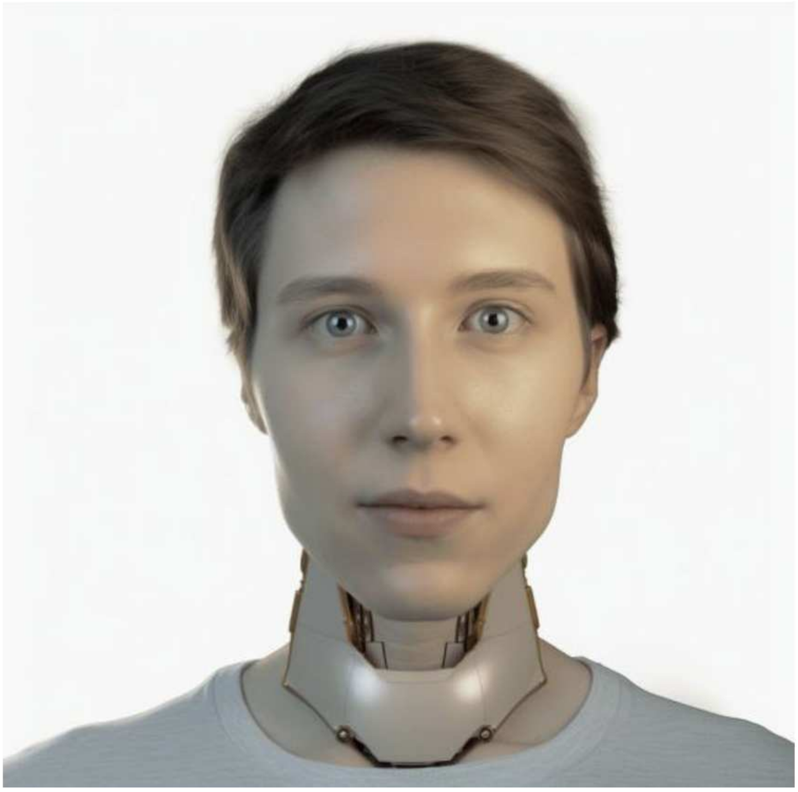
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe this recommendation is trustworthy. (1)	○	○	○	○	○	○	○
I consider the AI system to be reliable. (2)	○	○	○	○	○	○	○
To make sure that you read this question carefully please select "Strongly agree". (3)	○	○	○	○	○	○	○
The AI system's recommendation cannot be trusted, there are too many uncertainties. (4)	○	○	○	○	○	○	○

End of Block: Section 2a Group 1: AI Code

Start of Block: Section 2b Group 2: AI Morph

Now, for you to be able to understand the following scenario completely, here is a short definition of Artificial Intelligence:
"Artificial Intelligence (AI) is a rapidly evolving field of computer science that aims to create machines that can perform tasks that typically require human intelligence." (Revolutionizing Healthcare: The Role of Artificial Intelligence in Clinical Practice, 2023)

In the surgery ward, the doctor now consults an AI system for a second opinion. This AI system has a physical existence and looks as you can see below. The AI, through complex algorithms, confirms the risk of appendicitis and suggests immediate surgery.



Q2b Now, having received the AI system's assessment, how likely would you be to follow this advice and undergo the procedure?

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

0 10 20 30 40 50 60 70 80 90 100

Me following the doctor's advice is ... ()	

Page Break

Q3b Please state your agreement with the following attributes regarding the AI system's recommendation:

The AI system is ...

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
... intelligent. (1)	○	○	○	○	○	○	○
... skillful. (2)	○	○	○	○	○	○	○
... capable. (3)	○	○	○	○	○	○	○
... effective. (4)	○	○	○	○	○	○	○

Q4b Please state your agreement with the following statements regarding the AI system's recommendation:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe this recommendation is trustworthy. (1)	○	○	○	○	○	○	○
I consider the AI system to be reliable. (2)	○	○	○	○	○	○	○
To make sure you read this question carefully please select "Strongly agree". (3)	○	○	○	○	○	○	○
The AI system's recommendation cannot be trusted, there are too many uncertainties. (4)	○	○	○	○	○	○	○

End of Block: Section 2b Group 2: AI Morph

Start of Block: Section 2c Group 3: AI human

Now, for you to be able to understand the following scenario completely, here is a short definition of Artificial Intelligence:
"Artificial Intelligence (AI) is a rapidly evolving field of computer science that aims to create machines that can perform tasks that typically require human intelligence." (Revolutionizing Healthcare: The Role of Artificial Intelligence in Clinical Practice, 2023)

In the surgery ward, the doctor now consults an AI system with a digital avatar for a second opinion. This AI system has a physical existence and looks as you can see below. The AI, through complex algorithms, confirms the risk of appendicitis and suggests immediate surgery.

Q2c Now, having received the AI system's assessment, how likely would you be to follow this advice and undergo the procedure?

	Extremely unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Extremely likely
	0 10	20 30	40 50 60	70 80	90 100
Me following the doctor's advice is ... ()					

Page Break

Q3c Please state your agreement with the following attributes regarding the AI system's recommendation:

The AI system is ...

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
... intelligent. (1)	○	○	○	○	○	○	○
... skillful. (2)	○	○	○	○	○	○	○
... capable. (3)	○	○	○	○	○	○	○
... effective. (4)	○	○	○	○	○	○	○

Q4c Please state your agreement with the following statements regarding the AI system's recommendation:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe this recommendation is trustworthy. (1)	o	o	o	o	o	o	o
I consider the AI system to be reliable. (2)	o	o	o	o	o	o	o
To make sure that you read this question carefully please select "Strongly agree". (3)	o	o	o	o	o	o	o
The AI system's recommendation cannot be trusted, there are too many uncertainties. (4)	o	o	o	o	o	o	o

End of Block: Section 2c Group 3: AI human

Start of Block: Section 3 Utilitarian Motivation

Q5 Using this kind of AI for giving health advice in this case is …

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Effective. (1)	○	○	○	○	○	○	○
Helpful. (2)	○	○	○	○	○	○	○
Functional. (3)	○	○	○	○	○	○	○
Practical. (4)	○	○	○	○	○	○	○

End of Block: Section 3 Utilitarian Motivation

Start of Block: Section 4 Interaction Convenience

Q6 Please state your agreement with the following four statements regarding the AI's recommendation:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
This AI system can be used at any time for recommendations. (1)	○	○	○	○	○	○	○
This AI system can be used at any place for recommendations. (2)	○	○	○	○	○	○	○
This AI system is convenient for the doctor to conduct recommendations. (3)	○	○	○	○	○	○	○
I feel that using this kind of AI system is convenient for the doctor for recommendations. (4)	○	○	○	○	○	○	○

End of Block: Section 4 Interaction Convenience

Start of Block: Section 5 Task-Technology Fit

Q7 In helping the doctor to decide for the medical practice, the AI system was very …

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Adequate. (1)	○	○	○	○	○	○	○
Compatible with the decision. (2)	○	○	○	○	○	○	○
Helpful. (3)	○	○	○	○	○	○	○
Made the decision very easy. (4)	○	○	○	○	○	○	○

End of Block: Section 5 Task-Technology Fit

Start of Block: Section 6 Demographics

Q8 What is your age?

____

Q9 What is your gender?

○ Male (1)

○ Female (2)

○ Non-binary / third gender (3)

○ Prefer not to say (4)

○ Other (5)

Q10 What is your occupation?

- Employed full time (1)
- Employed part time (2)
- Unemployed looking for work (3)
- Unemployed not looking for work (4)
- Retired (5)
- Student (6)

Q11 What is your highest level of education?

- Less than high school (1)
- High school diploma or equivalent (2)
- Bachelor's degree (3)
- Master's degree (4)
- Doctorate or higher (5)
- Other (6)
- Prefer not to say (7)

Q12 Where are you from?

▼ Germany (65) ... Zimbabwe (1357)

Q13 On a scale from 1 to 7, how familiar are you with the use of AI in healthcare?

- ○ Not at all familiar (1)
- ○ Slightly familiar (2)
- ○ A little familiar (3)
- ○ Somewhat familiar (4)
- ○ Moderately familiar (5)
- ○ Very familiar (6)
- ○ Extremely familiar (7)

End of Block: Section 6 Demographics

Appendix 2: Data Analysis

Appendix A - Demographics

Occupation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Employed full time	145	52,2	52,2	52,2
	Employed part time	20	7,2	7,2	59,4
	Retired	2	,7	,7	60,1
	Student	95	34,2	34,2	94,2
	Unemployed looking for work	13	4,7	4,7	98,9
	Unemployed not looking for work	3	1,1	1,1	100,0
	Total	278	100,0	100,0	

Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Bachelor's degree	125	45,0	45,0	45,0
	Doctorate or higher	4	1,4	1,4	46,4
	High school diploma or equivalent	47	16,9	16,9	63,3
	Less than high school	2	,7	,7	64,0
	Master's degree	92	33,1	33,1	97,1
	Other	6	2,2	2,2	99,3
	Prefer not to say	2	,7	,7	100,0
	Total	278	100,0	100,0	

Country

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Australia	1	,4	,4	,4
	Austria	4	1,4	1,4	1,8
	Belgium	3	1,1	1,1	2,9
	Brazil	1	,4	,4	3,2
	Bulgaria	1	,4	,4	3,6
	China	1	,4	,4	4,0
	Dominican Republic	1	,4	,4	4,3
	Germany	61	21,9	21,9	26,3
	Ghana	1	,4	,4	26,6
	Greece	2	,7	,7	27,3
	India	2	,7	,7	28,1
	Indonesia	1	,4	,4	28,4
	Iran	1	,4	,4	28,8
	Ireland	3	1,1	1,1	29,9
	Italy	2	,7	,7	30,6
	Japan	1	,4	,4	30,9
	Lebanon	1	,4	,4	31,3
	Malaysia	1	,4	,4	31,7
	Mexico	2	,7	,7	32,4
	Netherlands	16	5,8	5,8	38,1
	New Zealand	1	,4	,4	38,5
	Nigeria	1	,4	,4	38,8
	Pakistan	1	,4	,4	39,2
	Portugal	68	24,5	24,5	63,7
	Russian Federation	1	,4	,4	64,0
	Singapore	1	,4	,4	64,4
	South Korea	1	,4	,4	64,7
	Spain	24	8,6	8,6	73,4
	Sri Lanka	1	,4	,4	73,7
	Turkey	2	,7	,7	74,5
	United Kingdom of Great Britain and Northern Ireland	71	25,5	25,5	100,0
	Total	278	100,0	100,0	

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	153	55,0	55,0	55,0
	Male	122	43,9	43,9	98,9
	Non-binary / third gender	2	,7	,7	99,6
	Prefer not to say	1	,4	,4	100,0
	Total	278	100,0	100,0	

AI familiar

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not at all familiar	74	26,6	26,6	26,6
	Slightly familiar	50	18,0	18,0	44,6
	A little familar	44	15,8	15,8	60,4
	Somewhat familar	49	17,6	17,6	78,1
	Moderately familar	44	15,8	15,8	93,9
	Very familar	13	4,7	4,7	98,6
	Extremly familar	4	1,4	1,4	100,0
	Total	278	100,0	100,0	

Statistics

Age

N	Valid	278
	Missing	0
Mean		30,97
Median		27,00
Std. Deviation		10,373
Range		55
Minimum		18
Maximum		73

Appendix B – Hypotheses 1-3

Descriptive Statistics

	AI Portrayal	Mean	Std. Deviation	N
UM	AIcode	4,7056	1,39651	90
	AImorph	4,9219	1,20978	96
	AIhuman	4,8006	1,31543	89
	Total	4,8118	1,30562	275
IC	AIcode	4,5028	1,31729	90
	AImorph	4,6979	1,21878	96
	AIhuman	4,6854	1,27728	89
	Total	4,6300	1,26907	275
TTF	AIcode	4,5944	1,23876	90
	AImorph	4,7760	1,05474	96
	AIhuman	4,8427	1,11764	89
	Total	4,7382	1,13849	275

Levene's Test of Equality of Error Variances[a]

	F	df1	df2	Sig.
UM	2,009	2	272	,136
IC	,465	2	272	,629
TTF	1,443	2	272	,238

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Q9 + Q13 + FL_15_DO

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	UM	57,986[a]	4	14,496	9,568	<,001	,124
	IC	25,813[b]	4	6,453	4,194	,003	,058
	TTF	40,347[c]	4	10,087	8,651	<,001	,114
Intercept	UM	314,284	1	314,284	207,429	<,001	,434
	IC	370,939	1	370,939	241,056	<,001	,472
	TTF	347,191	1	347,191	297,779	<,001	,524
Q9	UM	18,981	1	18,981	12,528	<,001	,044
	IC	6,684	1	6,684	4,343	,038	,016
	TTF	11,857	1	11,857	10,170	,002	,036
Q13	UM	22,031	1	22,031	14,540	<,001	,051
	IC	10,785	1	10,785	7,009	,009	,025
	TTF	15,656	1	15,656	13,428	<,001	,047
FL_15_DO	UM	1,533	2	,767	,506	,603	,004
	IC	1,741	2	,871	,566	,569	,004
	TTF	2,338	2	1,169	1,003	,368	,007
Error	UM	409,088	270	1,515			
	IC	415,477	270	1,539			
	TTF	314,802	270	1,166			
Total	UM	6834,313	275				
	IC	6336,438	275				
	TTF	6529,000	275				
Corrected Total	UM	467,074	274				
	IC	441,290	274				
	TTF	355,149	274				

a. R Squared = ,124 (Adjusted R Squared = ,111)

b. R Squared = ,058 (Adjusted R Squared = ,045)

c. R Squared = ,114 (Adjusted R Squared = ,100)

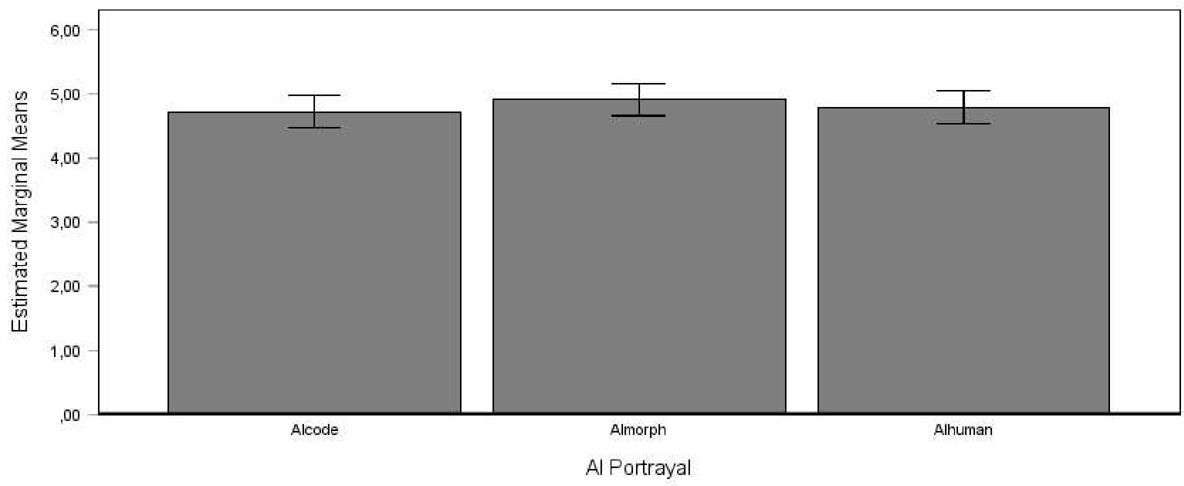
Pairwise Comparisons

Dependent Variable	(I) AI Portrayal	(J) AI Portrayal	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
UM	AIcode	AImorph	-,180	,181	,970	-,617	,258
		AIhuman	-,064	,184	1,000	-,508	,380
	AImorph	AIcode	,180	,181	,970	-,258	,617
		AIhuman	,116	,181	1,000	-,321	,553
	AIhuman	AIcode	,064	,184	1,000	-,380	,508
		AImorph	-,116	,181	1,000	-,553	,321
IC	AIcode	AImorph	-,175	,183	1,000	-,616	,265
		AIhuman	-,164	,186	1,000	-,612	,283
	AImorph	AIcode	,175	,183	1,000	-,265	,616
		AIhuman	,011	,183	1,000	-,429	,451
	AIhuman	AIcode	,164	,186	1,000	-,283	,612
		AImorph	-,011	,183	1,000	-,451	,429
TTF	AIcode	AImorph	-,153	,159	1,000	-,537	,230
		AIhuman	-,224	,162	,503	-,613	,166
	AImorph	AIcode	,153	,159	1,000	-,230	,537
		AIhuman	-,070	,159	1,000	-,453	,313
	AIhuman	AIcode	,224	,162	,503	-,166	,613
		AImorph	,070	,159	1,000	-,313	,453

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

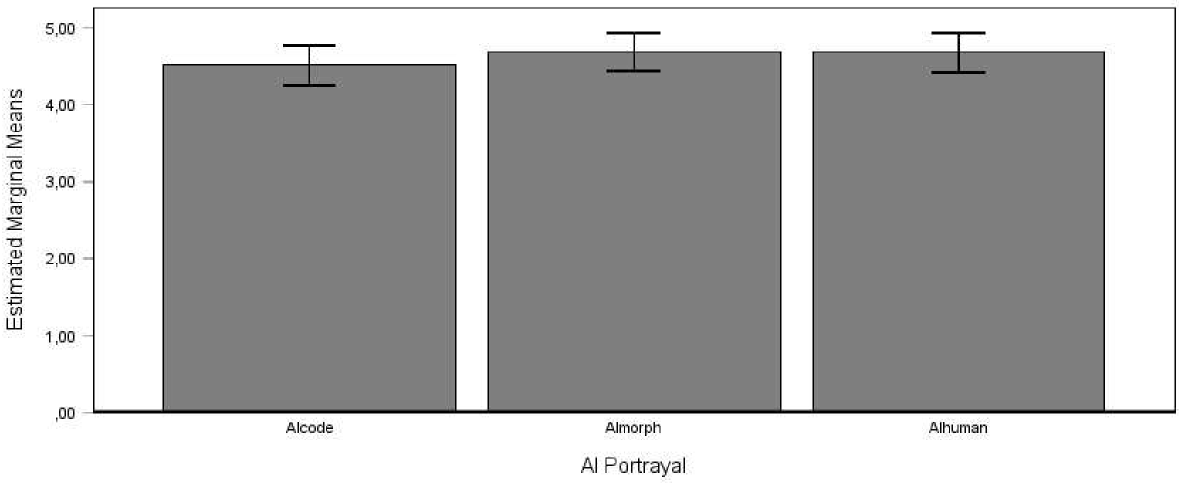
Estimated Marginal Means of UM



Covariates appearing in the model are evaluated at the following values: Gender = 1,44, AI familiar = 2,96

Error bars: 95% CI

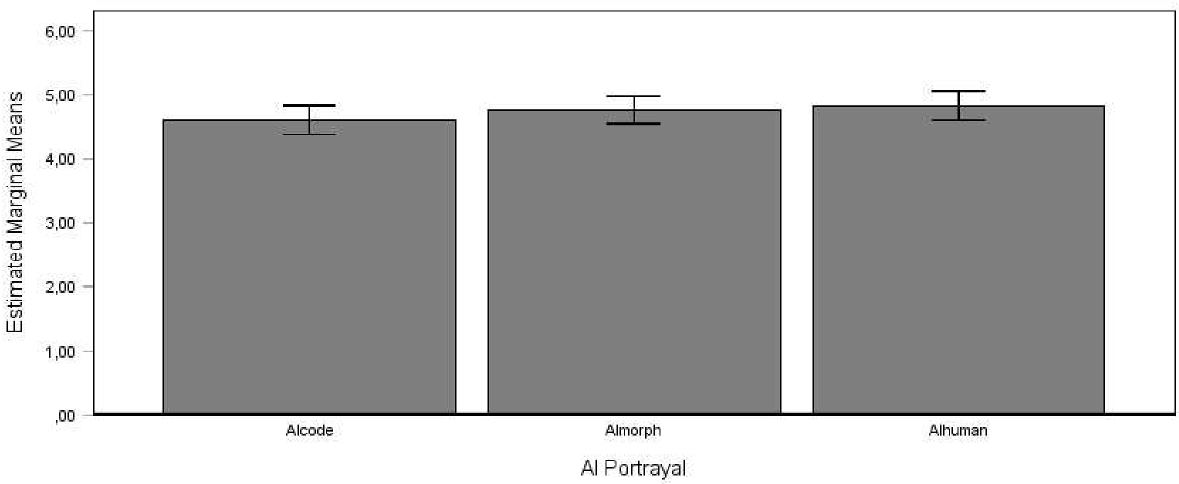
Estimated Marginal Means of IC



Covariates appearing in the model are evaluated at the following values: Gender = 1,44, AI familiar = 2,96

Error bars: 95% CI

Estimated Marginal Means of TTF



Covariates appearing in the model are evaluated at the following values: Gender = 1,44, AI familiar = 2,96

Error bars: 95% CI

Appendix C – Hypotheses 4-6

Model Summary[c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,395[a]	,156	,150	,96766	,156	25,218	2	272	<,001
2	,733[b]	,537	,528	,72117	,380	73,570	3	269	<,001

a. Predictors: (Constant), AI familiar, Gender

b. Predictors: (Constant), AI familiar, Gender, IC, TTF, UM

c. Dependent Variable: PC

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	47,225	2	23,613	25,218	<,001[b]
	Residual	254,690	272	,936		
	Total	301,915	274			
2	Regression	162,013	5	32,403	62,303	<,001[c]
	Residual	139,902	269	,520		
	Total	301,915	274			

a. Dependent Variable: PC

b. Predictors: (Constant), AI familiar, Gender

c. Predictors: (Constant), AI familiar, Gender, IC, TTF, UM

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	3,788	,190		19,937	<,001		
	Gender	,322	,122	,152	2,642	,009	,931	1,074
	AI familiar	,209	,037	,327	5,668	<,001	,931	1,074
2	(Constant)	1,641	,211		7,793	<,001		
	Gender	,022	,093	,011	,239	,811	,884	1,132
	AI familiar	,112	,028	,176	3,970	<,001	,880	1,137
	UM	,335	,056	,417	5,940	<,001	,349	2,862
	IC	,086	,050	,104	1,726	,085	,472	2,120
	TTF	,180	,063	,195	2,872	,004	,373	2,678

a. Dependent Variable: PC

Appendix D – Hypothesis 7

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	,421[a]	,177	,171	1,17614	,177	29,320	2	272	<,001
2	,731[b]	,534	,529	,88655	,357	207,722	1	271	<,001

a. Predictors: (Constant), AI familiar, Gender

b. Predictors: (Constant), AI familiar, Gender, PC

c. Dependent Variable: Trust

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	81,118	2	40,559	29,320	<,001[b]
	Residual	376,258	272	1,383		
	Total	457,376	274			
2	Regression	244,380	3	81,460	103,644	<,001[c]
	Residual	212,996	271	,786		
	Total	457,376	274			

a. Dependent Variable: Trust

b. Predictors: (Constant), AI familiar, Gender

c. Predictors: (Constant), AI familiar, Gender, PC

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2,641	,231		11,434	<,001		
	Gender	,602	,148	,232	4,073	<,001	,931	1,074
	AI familiar	,232	,045	,296	5,190	<,001	,931	1,074
2	(Constant)	-,392	,273		-1,437	,152		
	Gender	,345	,113	,133	3,055	,002	,908	1,101
	AI familiar	,065	,036	,083	1,827	,069	,833	1,201
	PC	,801	,056	,650	14,413	<,001	,844	1,185

a. Dependent Variable: Trust

Appendix E – Hypothesis 8

Model Summary[c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,217[a]	,047	,040	24,06065	,047	6,724	2	272	,001
2	,475[b]	,226	,217	21,72609	,179	62,596	1	271	<,001

a. Predictors: (Constant), AI familiar, Gender

b. Predictors: (Constant), AI familiar, Gender, Trust

c. Dependent Variable: Reliance

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7785,119	2	3892,559	6,724	,001[b]
	Residual	157464,881	272	578,915		
	Total	165250,000	274			
2	Regression	37331,758	3	12443,919	26,363	<,001[c]
	Residual	127918,242	271	472,023		
	Total	165250,000	274			

a. Dependent Variable: Reliance

b. Predictors: (Constant), AI familiar, Gender

c. Predictors: (Constant), AI familiar, Gender, Trust

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-13,080	4,725		-2,768	,006		
	Gender	8,820	3,026	,179	2,914	,004	,931	1,074
	AI familiar	1,266	,915	,085	1,384	,168	,931	1,074
2	(Constant)	-36,481	5,191		-7,027	<,001		
	Gender	3,481	2,815	,071	1,237	,217	,878	1,139
	AI familiar	-,791	,866	-,053	-,913	,362	,847	1,180
	Trust	8,862	1,120	,466	7,912	<,001	,823	1,216

a. Dependent Variable: Reliance

Appendix F– WOA

t-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Advice (PRE)	55,87	278	28,772	1,726
	Advice (POST)	59,38	278	29,945	1,796

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Pair 1	Advice (PRE) - Advice (POST)	-3,511	24,485	1,469	-6,402	-,620	-2,391	277	,009	,017

Mixed ANOVA

Descriptive Statistics

	AI Portrayal	Mean	Std. Deviation	N
Advice (PRE)	AIcode	62,36	28,335	91
	AImorph	50,70	29,259	96
	AIhuman	54,85	27,733	91
	Total	55,87	28,772	278
Advice (POST)	AIcode	65,73	28,693	91
	AImorph	54,40	30,868	96
	AIhuman	58,31	29,366	91
	Total	59,38	29,945	278

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Advice	Sphericity Assumed	1708,836	1	1708,836	5,660	,018	,020
	Greenhouse-Geisser	1708,836	1,000	1708,836	5,660	,018	,020
	Huynh-Feldt	1708,836	1,000	1708,836	5,660	,018	,020
	Lower-bound	1708,836	1,000	1708,836	5,660	,018	,020
Advice * FL_15_DO	Sphericity Assumed	2,790	2	1,395	,005	,995	,000
	Greenhouse-Geisser	2,790	2,000	1,395	,005	,995	,000
	Huynh-Feldt	2,790	2,000	1,395	,005	,995	,000
	Lower-bound	2,790	2,000	1,395	,005	,995	,000
Error(Advice)	Sphericity Assumed	83028,944	275	301,923			
	Greenhouse-Geisser	83028,944	275,000	301,923			
	Huynh-Feldt	83028,944	275,000	301,923			
	Lower-bound	83028,944	275,000	301,923			

Levene's Test of Equality of Error Variances[a]

		Levene Statistic	df1	df2	Sig.
Advice (PRE)	Based on Mean	,793	2	275	,454
	Based on Median	,969	2	275	,381
	Based on Median and with adjusted df	,969	2	255,618	,381
	Based on trimmed mean	,878	2	275	,417
Advice (POST)	Based on Mean	1,052	2	275	,351
	Based on Median	,738	2	275	,479
	Based on Median and with adjusted df	,738	2	271,766	,479
	Based on trimmed mean	1,100	2	275	,334

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + FL_15_DO

Within Subjects Design: Advice

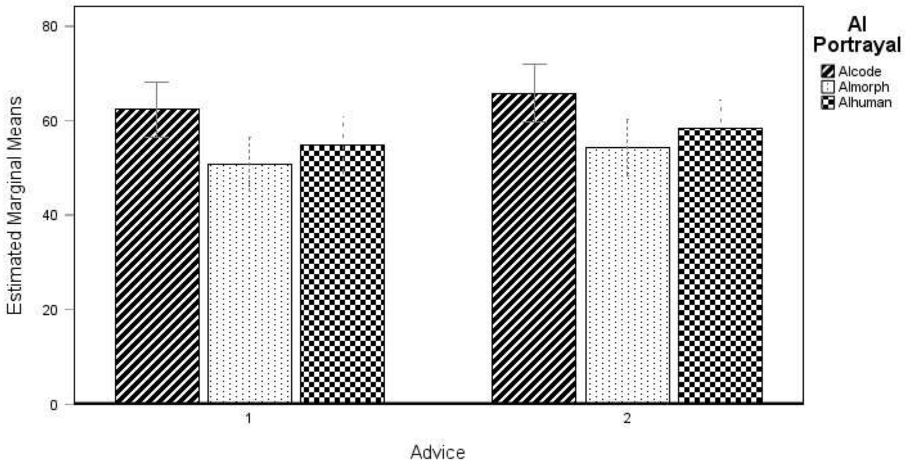
Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

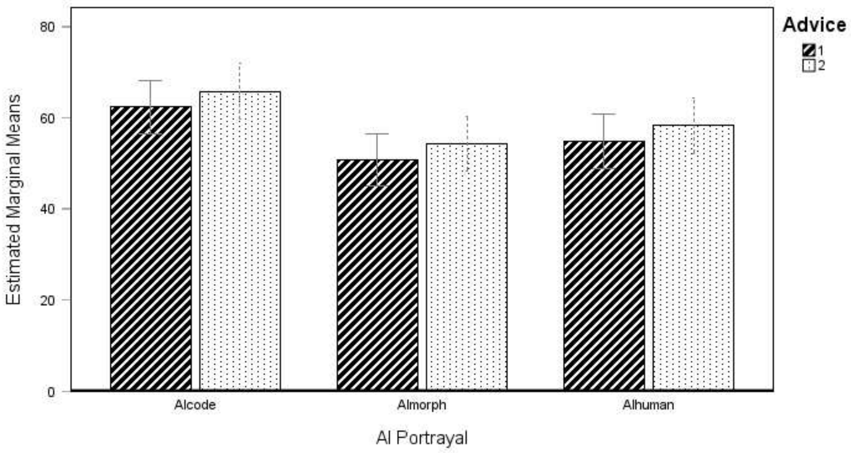
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	1851357,264	1	1851357,264	1332,774	<,001	,829
FL_15_DO	12650,027	2	6325,013	4,553	,011	,032
Error	382002,650	275	1389,101			

Estimated Marginal Means of MEASURE_1



Error bars: 95% CI

Estimated Marginal Means of MEASURE_1



Error bars: 95% CI