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Smart Health: How Culture Influences AI Adoption in the Healthcare System

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Master in Psychology of Intercultural Relations

Dr. Cristina Maria Lopes Camilo, Invited Assistant Professor, ISCTE - Instituto Universitário de Lisboa

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CIÊNCIAS SOCIAIS
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Department of Social and Organizational Psychology

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To my beloved mother, whose strength has been my guiding light.

Your belief in me has made this journey possible,

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I would like to extend my deepest gratitude to my supervisor, Dr. Cristina Camilo, for guidance and support that have been indispensable throughout this research journey. Her insightful feedback and patience have been of great importance to guide me in this work.

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Resumo

O presente estudo investiga os factores que influenciam a adoção de Sistemas de Apoio à Decisão Clínica com Inteligência Artificial (AI-CDSS) entre os médicos dos sistemas de saúde da Suíça e de Portugal, centrando-se nas dimensões culturais e psicológicas que moldam as intenções comportamentais. O desenho utilizado é um inquérito quantitativo, transversal, destinado a compreender a relação entre os valores culturais, em particular a evitação da incerteza, e factores-chave como as normas subjectivas e a perceção da crise de substituição que influenciam a adoção da IA.

A metodologia envolveu um inquérito distribuído a clínicos de instituições de cuidados de saúde de ambos os países, utilizando uma escala de Likert de sete pontos para avaliar variáveis como a utilidade percebida, as normas subjectivas e a prevenção da incerteza. Foram utilizadas técnicas de análise de regressão e de bootstrapping para avaliar as relações entre estas variáveis.

Os resultados revelaram que as Normas Subjectivas (SN) influenciam positivamente as Intenções Comportamentais (BI), embora este efeito não seja estatisticamente significativo, e que a Evitação da Incerteza (PSC) modera esta relação. Os indivíduos com menor Evitação da Incerteza apresentam uma ligação mais forte entre as normas subjectivas e as intenções comportamentais, enquanto os indivíduos com maior Evitação da Incerteza apresentam um efeito mais fraco. Além disso, os médicos que consideram a IA útil sentem-se menos ameaçados pela potencial crise de substituição, confirmando que a Utilidade Apercebida (PU) da IA reduz a Crise de Substituição Apercebida (PSC) ou o medo da substituição. No entanto, a Evitação da Incerteza aumenta ligeiramente a Crise de Substituição Apercebida, embora este efeito seja apenas marginalmente significativo. Embora o individualismo/coletivismo (IC) não modere a relação entre a Utilidade Apercebida e a Intenção Comportamental, modera o impacto das Normas Subjectivas, com os indivíduos orientados para o coletivismo a sentirem efeitos mais fortes.

Abstract

The present study investigates the factors that influence the adoption of Artificial Intelligence Clinical Decision Support Systems (AI-CDSS) among physicians in healthcare systems in Switzerland and Portugal, focusing on the cultural and psychological dimensions that shape behavioral intentions. The design employed is a quantitative, cross-sectional survey aimed at understanding the relationship between cultural values, particularly uncertainty avoidance, and key factors such as subjective norms and perceived substitution crisis in influencing AI adoption.

The methodology involved a survey distributed to clinicians in healthcare institutions in both countries, using a seven-point Likert scale to evaluate variables such as perceived usefulness, subjective norms, and uncertainty avoidance. Regression analysis and bootstrapping techniques were employed to assess the relationships between these variables.

The results revealed that Subjective Norms (SN) positively influence Behavioral Intentions (BI), though this effect is not statistically significant, and Uncertainty Avoidance (AU) moderates this relationship. Individuals with lower Uncertainty Avoidance show a stronger link between subjective norms and behavioral intentions, while those with higher Uncertainty Avoidance experience a weaker effect. Additionally, clinicians who view AI as useful feel less threatened by the potential substitution crisis, confirming that Perceived Usefulness (PU) of AI reduces Perceived Substitution Crisis (PSC) or fear of replacement. However, Uncertainty Avoidance slightly increases Perceived Substitution Crisis, though this effect is only marginally significant. While individualism/collectivism (IC) does not moderate the relationship between Perceived Usefulness and Behavioral Intention, it does moderate the impact of Subjective Norms, with collectivist-oriented individuals experiencing stronger effects.

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Introduction

Nell Watson (2024., p. 5) defines Artificial Intelligence (AI) as a "branch of computer science dedicated to develop machines that can perform tasks that traditionally require human intelligence. This includes learning, natural language understanding and various forms of resoning". In its early days, AI was integrated into health care to mimic human cognitive abilities in supporting medical professionals with diagnosis and treatment of their patients as much as possible. Particularly, the early progress was impressive in such areas as oncology, neurology, and cardiology, in which techniques from machine learning and natural language processing were applied (Jiang et al., 2017).

Over time, AI has transformed the medical field and has been included as part of different healthcare applications, such as diagnosis, treatment planning, robot-assisted surgeries, and pharmaceutical research. Currently, AI-powered devices and software, such as CDSS, help health professionals work with large datasets to improve the decision-making process. These systems rely on advanced techniques such as deep learning and neural networks to detect diseases, interpret genetic data, and forecasting patient outcomes (Jiang et al., 2017).

As we look to the future, AI is poised to revolutionize predictive analytics, precision medicine, and personalized healthcare. One key development involves continuous patient monitoring through wearable devices, with AI analyzing large datasets to enable early disease detection and suggest individualized treatments. However, to fully realize the potential of these technologies, challenges related to regulatory frameworks and data sharing must be addressed (Jiang et al., 2017).

While the technical advancements of AI are significant, its successful integration into clinical settings depends not only on these innovations but also on cultural and psychological factors. Cultural values, such as uncertainty avoidance and individualism versus collectivism, significantly influence how quickly healthcare professionals adopt AI technologies. For instance, in countries with high uncertainty avoidance, like Portugal, there is often hesitance towards adopting AI due to discomfort with ambiguity. Conversely, in lower uncertainty avoidance cultures, such as Switzerland, professionals may be more open to AI technologies, reflecting a greater willingness to embrace innovation and risk.

Psychological factors also play a critical role. Perceptions around AI, such as subjective norms and concerns over the perceived substitution crisis—the fear that AI might replace human expertise—can shape healthcare professionals' attitudes toward adoption. These factors determine whether AI is seen as a supportive tool or a threat to professional autonomy, thus influencing its acceptance.

To address these barriers, the traditional Technology Acceptance Model (TAM) develop by Davis (1989), which focuses on perceived usefulness and ease of use, must be expanded. A more comprehensive framework that incorporates cultural dimensions like uncertainty avoidance and psychological concerns such as the substitution crisis is essential to fully understand AI adoption in healthcare. By considering both the technical benefits of AI and the cultural-psychological barriers, a deeper understanding of its integration into clinical environments can be achieved.

In conclusion, while AI-driven Clinical Decision Support Systems hold the potential to revolutionize healthcare through improved decision-making and personalized care, their successful adoption will depend on overcoming cultural and psychological barriers. This dissertation aims to explore how these factors shape the acceptance of AI in healthcare, offering insights into optimizing AI integration across diverse clinical settings.

CHAPTER 1

Literature Review

1.1. The Role of AI in Healthcare and Clinical Decision Support Systems (CDSS)

AI has significantly transformed the medical field, finding applications in areas such as diagnosis, treatment planning, robot-assisted surgeries, and pharmaceutical research. AI-based Clinical Decision Support Systems (CDSS) have become integral in assisting healthcare professionals by analyzing vast amounts of data to improve decision-making processes. These systems utilize advanced AI techniques, such as deep learning and neural networks, to detect diseases, interpret genetic data, and predict patient outcomes (Jiang et al., 2017). CDSS systems help healthcare professionals with diagnostic assistance, recommending treatment protocols, and predicting treatment outcomes through the integration of symbolic reasoning and machine learning approaches, such as deep learning, to represent and infer medical knowledge efficiently (Jovic et al., 2020).

Despite its numerous benefits, such as improving clinical decision-making and reducing healthcare costs, AI-CDSS adoption is hindered by several challenges. A significant barrier is interpretability, which refers to the ability of clinicians to understand and trust AI system outputs. Clinicians must comprehend the rationale behind AI-generated decisions to fully embrace these systems (Xu et al., 2023). Another critical concern is the "black-box" nature of many AI models, making them opaque and difficult to understand. This opacity reduces accountability and trust among users (Watson, 2024). Bias in AI algorithms present another risk, potentially leading to inequitable care (Sutton et al., 2020). Additionally, system maturity, particularly in the choice and implementation phases, remains an issue (Hak et al., 2022).

CDSS has demonstrated the potential to improve clinician performance and patient outcomes (Johnston, 1994), yet future success will depend on addressing issues related to patient safety, quality, and equitable access to resources (El-Gayar et al., 2008). Another non-technical barrier is the professional resistance of healthcare providers, who may see these systems as a threat to their autonomy, especially if they perceive AI as undermining their clinical judgment. This fear of "losing face" or compromising professional authority exacerbates the hesitancy to adopt AI-CDSS (Sambasivan et al., 2012; Liang & Xue, 2021).

However, if the developed AI applications are not accepted by physicians, the potential benefits of AI will be significantly diminished (Liu et al., 2022). Montani and Striani (2019) identify this as a critical issue in healthcare settings, emphasizing that transparency and the ability to understand AI outputs are essential for gaining the trust of healthcare professionals, particularly in complex clinical decision-making environments. Institutions at the forefront of AI development, such as those in Switzerland, stand to benefit from research that prioritizes the creation of AI systems that are not only efficient but also interpretable. This focus on explainability addresses concerns about the opaque nature of AI, as Liu et al. (2022) points out, contributing to the faster and more confident adoption of AI technologies. Ensuring that healthcare professionals can effectively interpret AI-driven recommendations is crucial for building trust and ensuring the successful integration of AI into clinical practice.

1.2. Technology Adoption Models in Healthcare

The Technology Acceptance Model (TAM), introduced by Davis in 1989, is one of the most widely used models for explaining how individuals come to accept and use technology. The model postulates that two main factors influence the adoption of technology: Perceived Usefulness (PU), which is the degree to which a person believes that using a technology will improve their job performance, and Perceived Ease of Use (PEOU), which refers to the extent to which a person believes that using the technology will be free from effort (Davis, 1989). Both PU and PEOU directly influence the user's Behavioral Intention to adopt the technology, which, in turn, affects actual usage. TAM is particularly relevant in understanding how attitudes towards AI-CDSS in healthcare are shaped by perceived advantages in job performance (Davis, 1989).

The meta-analysis by Tao et al. (2019) extends this understanding by exploring the acceptance of consumer-oriented health information technologies (CHIT) within the TAM framework. The findings underscore that Perceived Usefulness has a significant positive effect not only on Behavioral Intention but also on users' attitudes toward CHIT, indicating that users are more likely to adopt CHITs when they perceive clear and substantial benefits, such as improved personal health management or enhanced access to health information.

In addition to TAM, other models like the Unified Theory of Acceptance and Use of Technology (UTAUT) extend the basic principles of TAM by incorporating additional factors such as Social Influence and Facilitating Conditions. These variables emphasize the role of external influences, such as peer opinions and organizational support, on an individual's decision to adopt new technology. Subjective Norms, for example, are important in environments like healthcare, where social norms within can heavily impact the adoption of AI-CDSS (Venkatesh & Davis, 2000).

1.3. Cultural Dimensions and AI Adoption

This study examines the cultural factors, specifically using Hofstede's framework on cultural dimensions, that influence the adoption of AI Clinical Decision Support Systems (AI-CDSS) in healthcare, which highlight how national cultural values shape professionals' openness to technology and perceptions of risk.

Geert Hofstede's (1980) framework on Cultural Dimensions provides insight into how national cultures influence the adoption of technology. Especially, two dimensions are most pertinent to AI adoption in healthcare, Uncertainty Avoidance (UA) and Individualism vs. Collectivism (IC). A complementary framework to understand the acceptance of new technologies, including AI, by clinicians is the Technology Acceptance Model (TAM) original ly proposed by Davis in 1989. TAM postulates that two principal factors, namely, perceived usefulness (PU) and perceived ease of use (PEOU), largely influence technology adoption behavior (Davis, 1989).

Uncertainty Avoidance (UA) reflects a society's tolerance for ambiguity. Cultures high in uncertainty avoidance are generally resistant to change and may view new technologies as a threat to stability because AI is inherently unpredictable in its decision-making algorithms and learning-based adjustments. As Raap et al. (2010) note, high UA cultures emphasize clear regulations and standardization, so professionals will seek reassurance that new technologies will fit in with existing protocols before adoption.

The cultural dimensions of Individualism versus Collectivism (IC) play a critical role in shaping attitudes toward technology adoption, especially in aemerging field such as Artificial Intelligence (AI). In individualistic societies, there is a huge appreciation for personal independence and self-expression are prioritized, which creates an enabling environment that is more open to new and potentially disruptive technologies (Hofstede, 2001). In contrast, collective societies emphasize group cohesion and social harmony, which may slow down the adoption rate of AI-based innovations since they adhere more closely to established group norms.

A society's orientation toward or against rapid technological change may also be influenced by its tolerance for uncertainty. According to Hofstede's work (2001) cultures with low Uncertainty Avoidance, such as Switzerland, usually have a higher acceptance of innovation and embrace new technologies, at a faster pace. Such societies are comfortable navigating novel situations and, therefore, be more adaptable to changes brought about by new technology. On the contrary, a culture with high Uncertainty Avoidance, like Portugal, demonstrate a more cautious approach, it seeks stability and predictability. Hence, there might be resistance toward the acceptance of new technologies, reflecting a cultural preference for established practices and routines.

Srite and Karahanna (2006) further explored how individual-level cultural values, particularly those related to IC, impact the acceptance of information technologies (IT). Their research analyzed how individual cultural values moderate three key relationships: the impact of subjective norms on the intention to use IT, the perceived usefulness of IT on behavioral intention, and the perceived ease of use on behavioral intention. Their findings highlight that in individualistic cultures, where personal benefit and autonomy are emphasized, perceived usefulness may play a more significant role in motivating adoption. Conversely, in collectivist cultures, the influence of subjective norms, which refers to perceptions about others' views, on IT use may have a stronger impact, reflecting the importance of aligning with group expectations. This nuanced understanding underscores that cultural values, including individualism/collectivism and uncertainty avoidance, are instrumental in shaping not only attitudes toward technology but also the pace and manner in which new technologies, such as AI, are integrated into society.

1.4. Differences Between Portugal and Switzerland on AI Adoption and Cultural Values

The adoption of AI in healthcare in Portugal and Switzerland reflects significant cultural differences, particularly in terms of institutional support, perceptions of AI's role, uncertainty avoidance and individualism. Although is important to acknowledge that the reason for collecting data in both Portugal and Switzerland is to ensure a broader range of responses by capturing variance in cultural and psychological factors influencing AI adoption in healthcare. By selecting two countries with distinct cultural profiles, the study aims to explore different perspectives and behaviors regarding AI adoption, which helps increase the diversity and richness of the data.

Institutional support also plays a crucial role in the differing levels of AI adoption in these two countries. In Portugal, the lack of AI-related education and training within medical curricula contributes to a slower uptake of AI technologies, as healthcare professionals feel less confident in using AI-based decision support systems (Pedro et al., 2023). Conversely, Switzerland benefits from strong institutional backing, with universities like ETH Zurich and EPFL leading advancements in AI research. These institutions collaborate closely with the private sector, facilitating the development and integration of AI tools into healthcare (Dessimoz et al., 2015).

The perceived role of AI in healthcare varies between the two countries. In Portugal, there is widespread concern that AI could lead to the dehumanization of healthcare, with professionals wary that technology might undermine the personal interactions between doctors and patients. As a result, there is reluctance to rely on AI for critical diagnostic or therapeutic tasks (Pedro et al., 2023). In contrast, Swiss healthcare professionals operate in a more innovation-friendly environment (Dessimoz, 2015), potentially benefiting this perception positively. Swiss employees are optimistic about the role of AI, with nearly 69% believing that it will positively impact their careers, enabling them to adapt to future roles (Müller, 2024).

1.4.1. Uncertainty Avoidance

A study by Pedro et al. (2023) examined the perceptions of AI's overall impact on clinical practice proposed that medical doctor in Portugal exhibit caution toward AI adoption, particularly due to concerns over job displacement and replacement by automation. Most respondents expressed confidence that their specific roles would not be replaced by AI. However, they also voiced concerns about potential resentment among medical doctors, who fear that AI may threaten their job security within clinical practice. Additionally, many respondents acknowledged the possibility of AI replacing other healthcare roles as well.

Although many professionals believe their specific roles will not be replaced, they recognize the risk for certain professions within healthcare, leading to caution in adopting AI. This concern aligns with Portugal's high Uncertainty Avoidance Index (UAI score of 104). Furthermore, the reduced ability to improvise when using AI and fears of losing human intuition in healthcare are central to the slower adoption pace (Pedro et al., 2023).

In contrast, Switzerland's lower uncertainty avoidance (UAI score of 58) reflects a more open attitude toward change and innovation. This aligns with Hofstede's (2001) findings that societies with high UA are slower to adopt new technologies, especially those that introduce ambiguity in decision-making processes, such as AI systems. In fact, Switzerland is leading Europe in AI workforce adoption, with 32% of Swiss employees already using AI in their roles, compared to a European average of 23% (Müller, 2024).

Moreover, the role of subjective norms in high-UA contexts like Portugal can further exacerbate reluctance toward AI adoption. Drawing on Hwang and Lee (2012), who demonstrated that uncertainty avoidance moderates the impact of subjective norms on cognition-based trust elements (such as integrity and ability), we see that high-UA cultures tend to place greater trust in established practices and social consensus when adopting new technologies. For Portuguese clinicians, subjective norms may reinforce a conservative stance toward AI, potentially due to a perceived erosion of professional integrity or competency as AI tools introduce automated decision pathways. Though Hwang and Lee (2012) did not measure this relationship in healthcare or AI specifically, their findings underscore how high-UA cultures prioritize social validation and trust in decision-making, creating an additional layer of complexity when adopting disruptive technologies such as AI in healthcare settings.

1.4.2. Individualism vs. Collectivism

Portugal’s collectivist culture (IDV score of 27) emphasizes group decision-making and prioritizes human-centered care, which contributes to hesitancy in delegating healthcare tasks to AI systems (Pedro et al., 2023). Portuguese doctors are particularly reluctant to delegate tasks like obtaining medical histories to AI, citing the complexity of these interactions and the importance of direct communication and empathy in medical practice.

A study by Chew and Achananuparp (2021) exemplifies the influence of empathy on AI adoption in healthcare, examining perceptions and needs related to AI integration. Stakeholders, particularly healthcare providers, noted that AI's lack of human-like empathy limits its ability to replace clinicians in contexts that require complex emotional support. There is recognition that AI could complement human care but not replace it fully, as true empathy includes understanding unspoken emotions and body language nuances that AI cannot yet interpret reliably to prevent it from feeling awkward or overly artificial.

This hesitation reflects the collective judgment that plays a central role in Portuguese healthcare, where institutional traditions and human relationships are prioritized over automation (Pedro et al., 2023). As a result, skepticism toward automating clinical tasks, especially those that involve patient interaction, is deeply rooted in the cultural value placed on face-to-face communication and the collective decision-making process in medical care.

Hofstede (2001) identified individualism as a major predictor of faster technology adoption, particularly in developed nations such as Switzerland, which, with a higher individualism score (IDV score of 68), fosters a culture of personal autonomy and responsibility.

These cultural scores are based on Hofstede's 2010 model updates, as reported by Hofstede Insights (https://www.hofstede-insights.com).

1.5. Attitudinal Factors Influencing Technology Adoption

Ajzen (1991) described attitudes as evaluations of an object or behavior with specific attributes or outcomes, which are valued positively or negatively. In technology contexts, attitudes can significantly impact user acceptance and adoption, particularly when examining subjective beliefs and norms toward a specific technology.

The Technology Acceptance Model (TAM), introduced by Davis (1989), is essential in understanding these factors. TAM suggests that two key determinants—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—influence users' attitudes toward technology. Perceived Usefulness is the extent to which a person believes using the technology will enhance their performance, while Perceived Ease of Use reflects the belief that using the technology will require minimal effort. Together, PU and PEOU shape attitudes and, subsequently, users' intentions and actual adoption of technology.

In their 2000 extension of the Technology Acceptance Model (TAM), Venkatesh and Davis integrated subjective norms to address the influence of social pressure on technology adoption. They posited that, beyond individual assessments of usefulness and ease of use, individuals might adopt a system to align with expectations from influential figures or peers. This addition acknowledges that social influence can play a critical role, particularly in mandatory environments, where users might feel compelled to adopt technology based on compliance with organizational norms rather than personal attitudes.

Subjective Norms refer to an individual's perception of whether people important to them believe they should use a particular technology. In healthcare settings, subjective norms can have a significant impact on AI-CDSS adoption. For example, in high UA cultures like Portugal, the influence of peers and authority figures plays a critical role in shaping behavioral intentions (Metallo et al., 2022). Social Influence has been demonstrated as a major factor in shaping initial trust in AI systems, particularly among healthcare professionals and students in a study conducted by Tran et al. (2021) with the objective of understand the factors influencing medical students' intentions to use an AI-based diagnosis support system, using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The research surveyed 211 medical students in Vietnam and found that social influence (the impact of peers, mentors, and respected professionals) was the most significant predictor of students' willingness to adopt AI technology. Although performance expectancy and effort expectancy were hypothesized to influence trust and intention, they were less impactful, likely due to the students' limited direct experience with AI systems in their training.

Resistance to AI in healthcare is often driven by psychological factors, including fear of job loss and discomfort with new technologies. Many physicians view AI-CDSS as a threat to their professional autonomy, fearing that these systems may replace or undermine their clinical judgment.

This concern is echoed in the findings of Sambasivan et al. (2012), who studied the adoption of CDSS in Malaysian hospitals and observed 450 physicians' perception of a threat to their autonomy significantly lowered their intention to use such systems. The research identified that physicians feared CDSS could restrict their control over clinical processes and limit their ability to apply personalized, experience-based decision-making.

1.6. Perceived Substitution Crisis

The Perceived Substitution Crisis (PSC) refers to concerns that technology will replace human workers in decision-making roles. This phenomenon is particularly relevant in healthcare, where professionals fear that AI-CDSS could substitute human expertise in clinical diagnoses and treatment planning. Tran et al. (2021) attributes this substitution crisis to concerns over job security, increasing reliance on AI, and the potential erosion of clinical decision-making skills. These worries are exacerbated in cultures with high levels of

Uncertainty Avoidance, where ambiguity and change are met with suspicion. Furthermore, Tran et al. argue that social influence significantly shapes attitudes toward AI. Specifically, when medical professionals perceive that their peers or institutional leaders endorse AI, they are more inclined to trust and adopt it.

This is consistent with the concerns outlined by Lambert et al. (2023), who highlight the reluctance of senior professionals. Due to their extensive experience, these individuals tend to be protective of their clinical judgment and cautious about adopting new technologies. Fan et al. (2020) suggest that this reluctance stems from a perceived threat to their authority and expertise in clinical decision-making. Fan et al. further explain that healthcare professionals may view AI as a challenge to their diagnostic authority, which can lead to resistance in adopting AI-based systems.

The perception of AI as a substitute for human judgment can hinder technology adoption. However, the Perceived Usefulness (PU) of AI has been found to alleviate these concerns. Shamszare and Choudhury (2023) assert that when healthcare professionals believe AI enhances their job performance, the fear of substitution diminishes, leading to a greater willingness to adopt AI-CDSS. This is reinforced by both Tran et al. (2021) and Fan et al. (2020), who suggest that when AI is perceived as improving diagnostic accuracy and reducing workload, healthcare professionals' attitudes shift from fear to acceptance. Tran et al. emphasize that effort expectancy and social influence play a significant role in fostering initial trust in AI systems. This trust is crucial in overcoming the substitution crisis, as it helps professionals view AI as a complement to their expertise rather than a replacement. Similarly, Fan et al. suggest that when AI improves diagnostic precision, particularly in complex medical cases, professionals are more likely to integrate it into their practice.

Both Tran teal. (2021) and Fan et al. (2020) stress the importance of considering the cultural and organizational context when addressing the substitution crisis. Tran's et al. (2021), in particular, found that in cultures with high levels of Uncertainty Avoidance, such as Vietnam, professionals tend to be more skeptical of technological change. The fear of substitution is particularly pronounced in these settings. However, as Tran et al. notes, incorporating AI-related curricula and increasing exposure to AI technologies in medical education can mitigate these concerns by preparing future physicians to work alongside AI. Fan et al. (2020) similarly highlights that successful integration of AI into routine clinical practice requires addressing both the technical proficiency and psychological readiness of healthcare workers. AI must be framed as a tool that enhances, rather than replaces, clinical decision-making to reduce the perceived substitution crisis.

Lambert et al. (2023) provide additional evidence that senior professionals are wary of AI systems that might replace their clinical expertise. Their reluctance often stems from years of accumulated experience, which makes them more protective of their professional judgment and skills.

Ultimately, while the perception of AI as a substitute for human judgment can negatively impact technology adoption, the Perceived Usefulness of AI has the potential to mitigate these concerns. When healthcare professionals recognize that AI can enhance their job performance, they are more likely to embrace AI-CDSS (Shamszare & Choudhury, 2023).

1.7. The present study

While the Technology Acceptance Model (TAM) effectively explains technology adoption based on PU and PEOU, it does not account for the cultural and psychological factors that influence adoption in complex environments like healthcare. For instance, Subjective Norms were not part of the original TAM, but later adaptations, such as TAM2, incorporated them as key variables (Venkatesh & Davis, 2000).

This study proposes an enhanced version of TAM, which integrates Perceived Substitution Crisis (PSC), Uncertainty Avoidance (UA), and Subjective Norms (SN). The inclusion of these variables addresses the limitations of the traditional TAM by considering how cultural values and psychological resistance shape behavioral intentions towards AI-CDSS adoption. For example, in cultures with high UA, the relationship between SN and Behavioral Intention is likely to be stronger due to reliance on established norms and resistance to uncertainty (Srite & Karahanna, 2006; Metallo et al., 2022)

1.8. Objectives and hypothesis

The present study aims to explore the influence of cultural and psychological factors on the adoption of AI-CDSS among healthcare professionals in Switzerland and Portugal. Specifically, it investigates how cultural values such as uncertainty avoidance and individualism versus collectivism impact behavioral intentions to adopt AI-CDSS. Additionally, it examines how subjective norms and the perceived substitution crisis (i.e., the concern that AI will replace human clinicians) interact with these cultural dimensions to influence adoption.

The study hypothesizes the following:

H1: Subjective norms positively affect behavioral intention to adopt AI-CDSS, suggesting that the social influence from peers and authority figures will increase clinicians' intention to use AI-CDSS.

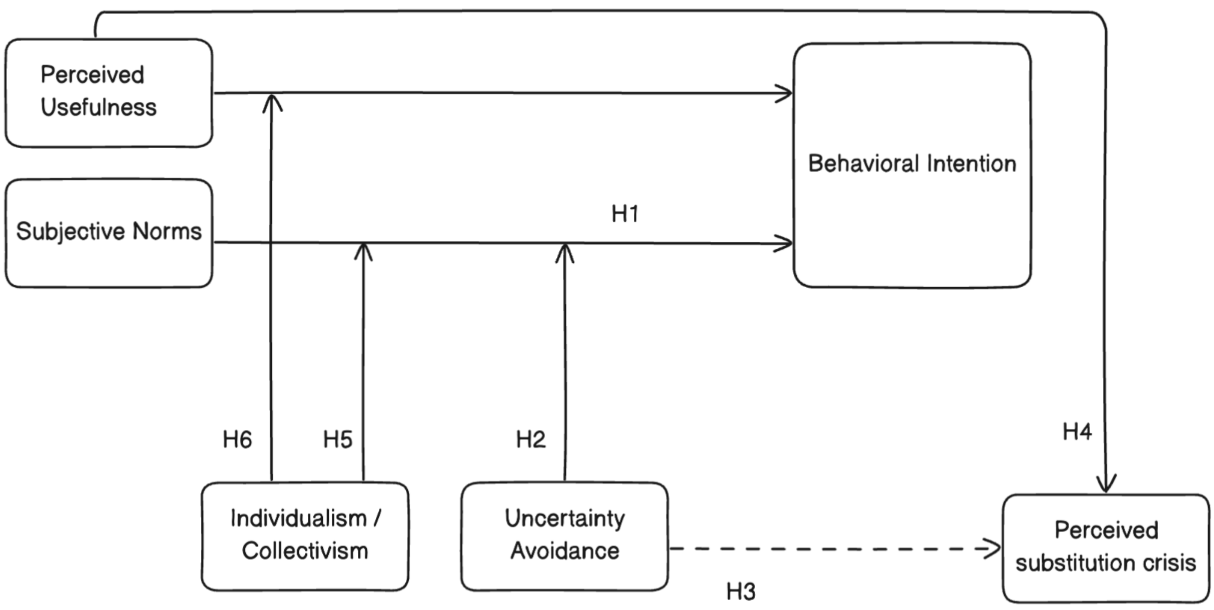
H2: The relationship between subjective norms and behavioral intention will be stronger for individuals with higher uncertainty avoidance, meaning that individuals who prefer stability and resist ambiguity are more influenced by social norms when deciding to adopt AI.

H3: Uncertainty avoidance is positively correlated with perceived substitution crisis, such that individuals with higher levels of uncertainty avoidance will perceive a greater threat that AI will replace human roles in clinical decision-making.

H4: There is an inverse relationship between clinicians' perceived usefulness of AI and their perceived substitution crisis, meaning that clinicians who see AI as useful are less likely to fear being replaced by it.

H5: Individualism versus collectivism moderates the relationship between subjective norms and behavioral intention. It is expected that collectivist cultures, which emphasize group harmony, will show a stronger relationship between subjective norms and behavioral intention than individualistic cultures.

H6: Individualism versus collectivism moderates the relationship between perceived usefulness and behavioral intention, with individualistic cultures showing a stronger relationship between the perceived usefulness of AI and the intention to adopt it.



Graphic 1
Research Model

CHAPTER 2

Methods

2.1. Design

This study employs a quantitative cross-sectional survey design to explore the factors influencing clinicians' intention to use AI-CDSS. The study aims to examine the relationships between key variables grounded in the TAM and Hofstede's (1980) cultural dimensions among clinicians in Portugal and Switzerland. The primary objective is to identify how factors like Perceived Usefulness, Subjective Norms, and cultural dimensions influence Behavioral Intention to adopt AI-CDSS. Additionally, the study investigates the moderating role of Individualism vs. Collectivism, Uncertainty Avoidance, and the Perceived Substitution Crisis on these relationships.

2.2. Participants

The target population consists of clinicians working or studying at healthcare and educational institutions in Portugal and Switzerland. Specifically, clinicians associated with both the University Hospital Zurich and Universidade de Minho were part of the sample. The total estimated population of clinicians across these institutions is approximately 1,500.

The target sample size was determined to be 65 participants, based on Cohen's formula for multiple regression analysis, considering a large effect size ($f^2 = 0.35$), an alpha level of 0.05, and a desired statistical power of 0.80.

Table 1
Sociodemographic Characteristics of Participants

	Total (N = 32)	
	n	%
Age Range		
24-35	4	12.5
36-45	12	37.5
46-55	9	28.1
56+	7	21.9
Gender		
Male	19	59.4
Female	13	40.6
Level of Education		
Master / Specialization	23	71.9
Ph.D.	8	25.0
IT Experience Level		
Beginner	3	9.4
Intermediate	11	34.4
Proficient	12	37.5
Expert	6	18.8

Participants are distributed across age groups, with the 36-45 age group comprising 37.5% of the sample. The gender distribution was balanced, with males representing 59.4% and females 40.6%.

Most participants hold a Master's degree or specialization. Regarding IT experience, participants show varied levels of proficiency. The largest groups are proficient (37.5%) and intermediate (34.4%) users. The distribution in IT experience provides a diverse sample in terms of digital competencies.

In summary, the sociodemographic profile represents a well-educated, predominantly middle-aged sample with a broad range of IT experience levels.

2.3. Materials and measures

The present study used a correlational, cross-sectional design The survey was provided in three languages—Portuguese, German, and English—to accommodate the linguistic diversity of the participating clinicians. Survey items were adapted from two foundational studies. Most items were based on and adapted from Metallo's et al. (2022) scale, which measures the following constructs: Behavioral Intention, Perceived Usefulness, Perceived Ease of Use (PEOU), Subjective Norms, Individualism, Uncertainty Avoidance, Long- and Short-Term Orientation (LT), and Power Distance (PD).

In addition to these items, the concept of perceived substitution crisis was drawn from Fan et al. (2020). This concept addresses concerns among healthcare professionals regarding the possibility of AI systems replacing their roles in medical diagnoses.

BI was measured using two items from an adapted scale based on Metallo et al. (2022). Participants indicated their agreement with statements reflecting their intention to use a system if access were provided, using a Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The items included: "Assuming I have access to the system, I intend to use it" (BI1) and "Given that I have access to the system, I predict that I would use it" (BI2). To calculate a BI score, responses were averaged across these two items. A Cohen's Weighted Kappa analysis revealed substantial agreement between the items ($\kappa = .86$, $p < .001$), indicating strong consistency in participant responses.

PU was assessed through four items adapted from Metallo et al. (2022), measuring participants' perceptions of the system's utility in enhancing their job performance. Participants rated their agreement with each statement on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). The items included: "Using the system will improve my performance in my job" (PU1), "Using the system in my job will increase my productivity" (PU2), "Using the system will enhance my effectiveness in my job" (PU3), and "I find the system to be useful in my job" (PU4). Responses were averaged to calculate a final PU score. The scale demonstrated high internal consistency, with a Cronbach's Alpha of .93, suggesting that all items contributed strongly to the perceived usefulness construct.

PEOU was measured with four items reflecting the degree to which participants found the system easy to use. Participants responded on a 7-point Likert scale, where higher scores indicated greater ease of use. The items were: "My interaction with the system is clear and understandable" (PEOU1), "Interacting with the system does not require a lot of my mental effort" (PEOU2), "I find the system to be easy to use" (PEOU3), and "I find it easy to get the system to do what I want it to do" (PEOU4). The items for this dimension were sourced from Metallo et al. (2022) and were averaged to calculate the final score. The scale showed acceptable internal consistency with a Cronbach's Alpha of .75 .

SN was evaluated using two items that measured the social influence on participants' decisions to use the system. Respondents indicated their agreement on a 7-point Likert scale. The items, sourced from Metallo et al. (2022), included: "People who influence my behavior think that I should use the system" (SN1) and "People who are important to me think I should use the system" (SN2). A Cohen's Weighted Kappa of 0.77 ($p < .001$) indicated substantial agreement between these two items, considering that items were averaged to calculate the final score, suggesting that participants' social circles played a consistent role in shaping their behavioral intentions.

IC was measured using four items aimed at understanding participants' orientation toward group versus individual priorities. Participants rated their agreement on a 7-point Likert scale, with higher scores reflecting stronger collectivist values. The items, sourced from Metallo et al. (2022) included: "Being accepted as a member of a group is more important than having autonomy and independence" (IC1), "Group success is more important than individual success" (IC2), "Being loyal to a group is more important than individual gain" (IC3), and "Individual rewards are not as important as group welfare" (IC4). To calculate a IC score, responses were averaged across these four items. The scale demonstrated good internal consistency (Cronbach's Alpha = .81).

UC was assessed through four items, each addressing participants' preferences for structure and predictability in the work environment. Participants responded on a 7-point Likert scale. The items, sourced from Metallo et al. (2022) included: "Rules and regulations are important because they inform workers what the organization expects of them" (UC1), "Order and structure are very important in a work environment" (UC2), "It is better to have a bad situation that you know about than to have an uncertain situation which might be better" (UC3), and "People should avoid making changes because things could get worse" (UC4). Items were averaged to calculate the final score. The scale had moderate reliability with a Cronbach's Alpha of .59, indicating some variability in responses across these items.

LT was measured using four items that evaluated participants' perspectives on tradition and future planning. The items were rated on a 7-point Likert scale, and higher scores reflected stronger long-term orientation. The items, sourced from Metallo et al. (2022) were: "Respect for tradition is important for me" (LT1), "I work hard for success in the future" (LT2), "Traditional values are important for me" (LT3), and "I plan for the long term" (LT4). The items were averaged to calculate the final score. The scale demonstrated good reliability with a Cronbach's Alpha of .76, suggesting a strong emphasis on long-term values and goals among participants.

PD was measured using four items that reflected participants' acceptance of hierarchical structures in decision-making processes. Responses were recorded on a 7-point Likert scale, with higher scores indicating greater acceptance of power distance. The items from Metallo et al. (2022) included: "Managers should make most decisions without consulting subordinates" (PD1), "Managers should not ask subordinates for advice because they might appear less powerful" (PD2), "Decision-making power should stay with top management and not be delegated to lower-level employees" (PD3), and "Employees should not question their manager’s decision" (PD4). To calculate a PD score, responses were averaged across these four items. The scale showed excellent reliability (Cronbach’s Alpha = .92).

PSC was assessed through four items sourced from Fan (2020) that measured concerns about AI systems potentially replacing human workers, specifically doctors. Participants responded on a 7-point Likert scale. The items were: "I think that AI-CDSS will likely replace doctors in the future" (PSC1), "I think using AI-CDSS for a long time would make doctors dependent on them" (PSC2), "I think the rise and development of AI-CDSS would likely lead to the unemployment of some doctors" (PSC3), and "I think using AI-CDSS for a long time would decrease doctors’ own diagnostic ability" (PSC4). Items were averaged to calculate scores. The scale had good internal consistency with a Cronbach’s Alpha of .80, indicating a general concern among participants about the long-term impact of AI on the medical profession.

2.4. Procedures

All materials for this study were approved by the Ethics Committee of ISCTE (19/04/2024). Data collection was conducted through an online survey administered via Qualtrics, which was distributed using three primary methods: email, social media, and posters. The posters included a QR code that directed participants to the online survey, while additional participants were recruited through LinkedIn.

Participants were first presented with an informed consent form, which detailed the researchers' contact information, the study's duration, and emphasized the voluntary, anonymous, and confidential nature of participation. Upon agreeing to the terms, participants accessed the debriefing that introduced and defined the AI-CDSS system, followed by a short video demonstrating an example. After viewing the video, participants completed the questionnaire, followed by demographic questions.

The survey targeted clinicians working in selected healthcare institutions in Portugal and Switzerland. It was self-administered, meaning participants filled out the survey independently without external assistance. Of the responses collected, 17 were excluded due to incomplete submissions. (Materials available in Appendix A-C).

CHAPTER 3

Results

This chapter presents the findings from the data analysis, addressing the research objectives and hypotheses outlined in the earlier chapters. The results are organized in a manner that aligns with the key research hypothesis and the structure of the study. Both descriptive and inferential statistics are used to summarize and analyze the data, providing insights into the relationships and patterns identified in the study. The analyses were performed using Statistical Package for Social Sciences (SPSS), version 29. Missing values were addressed through the listwise deletion method, and all statistical analyses were performed at a 95% confidence interval. Additionally, the Process macro was used to test for moderation effects.

3.1. Descriptive Analysis of the Variables

Firstly, a descriptive analysis of the data was conducted. Table 2 presents the mean, standard deviation values, skewness and kurtosis for the variables of Subjective Norms, Perceived Usefulness, Individualism vs. Collectivism, Uncertainty Avoidance, Perceived Substitution Crisis and Behavioral Intention.

Table 2

Descriptive Statistics of Study Variables

	N	Min	Max	Mean	Std. Dev	Skewness	Kurtosis	KS (Sig.)
Subjective Norms	32	1.00	7.00	3.67	1.33	-.22	-.27	<.001
Perceived Usefulness	32	2.50	7.00	5.20	1.21	-.58	.05	.131
Individualism/Colle	32	1.25	6.00	3.89	1.34	-.15	-.94	.827
Uncertainty Avoidance	32	2.75	6.25	4.46	.86	.26	-.49	.086
Perceived Substitution Crisis	32	1.00	6.25	3.33	1.47	.28	-.94	.046
Behavioral Intention	32	3.00	7.00	5.53	1.21	-.85	.31	.015

The descriptive statistics on the SN indicate a moderate level of SN among respondents. The negative skewness suggests a slight tendency towards higher values, while the KS test indicates a significant deviation from normality ($p < 0.001$). PU mean and standard deviation of 1.21, reflected a generally favorable perception of usefulness. The skewness indicates a tendency towards higher values, although the KS test suggests normality.

The mean score of IC suggests a balance between individualistic and collectivist tendencies, with a slight negative skewness and a KS test results indicating normality.

The average score of UA indicates moderate uncertainty avoidance, with a slight positive skewness and a marginally significant KS test.

The PSC mean score and positive skewness indicate some concern about substitution issues. The KS test shows significance, suggesting a deviation from normality.

Finally, BI mean score expresses strong behavioral intentions. The negative skewness suggests a tendency towards higher intentions, and the KS test result indicates significant non-normality.

3.2. Correlations between variables

Table 3

Pearson Correlation Values for Study Variables

	1.	2.	3.	4.	5.
1. Subjective Norms	-				
2. Perceived Usefulness	.42*	-			
3. Individualism/Colle	.32	.29	-		
4.Uncertainty Avoidance	-.34	-.27	.11	-	
5.Perceived Substitution Crisis	-.18	-.63**	-.11	.42*	-
6.Behavioral Intention	.29	.87**	.37*	-.34	-.59**

The analysis of the relationships among the study variables are presented in Table 3. Subjective Norms are positively associated with Perceived Usefulness and Behavioral Intention, indicating that when individuals feel that important others support a behavior, they are likely to find it more useful and intend to engage in it. PU strongly correlates with BI, suggesting that individuals who perceive a technology or behavior as useful are more inclined to express a strong intention to adopt it. Additionally, increased PU is linked to decreased concerns about substitution crises. IC shows positive relationships with both SN and BI, implying that cultural orientation may influence individuals' perceptions and intentions regarding behaviors. UAe negatively correlates with SN and BI, suggesting that higher levels of uncertainty avoidance are associated with weaker social support and lower intentions to engage in certain behaviors. PSC is positively associated with UA and negatively related to BI. This indicates that as concerns about substitution crises increase, individuals are less likely to express intentions to adopt new behaviors or technologies.

3.3. Association between Subjective Norms and Behavioral Intention (H1) and Uncertainty Avoidance moderation (H2).

To examine the indirect effects of SN on BI and the moderating effect of UA, we utilized the PROCESS macro Model 1 (Hayes, 2017). It was hypothesized that SN would positively influence BI (H1) and that this relationship would be stronger for individuals with higher levels of Uncertainty Avoidance, indicating a moderation effect (H2).

Bootstrapping with 5,000 resamples was applied to estimate the indirect effects, yielding bias-corrected confidence intervals to assess the significance of the mediated pathways.

Table 4

Moderation effect of Uncertainty Avoidance on the association between Subjective Norms and Behavioral Intention

	Behavioral Intention				
	b	se	t	p	CI
Subjective Norms (SN)	.24	.14	1.66	.108	[-0.06, 0.53]
Uncertainty Avoidance (UA)	-.63	.23	-2.69	.012	[-1.11, -0.15]
SN*UA	-.28	.14	-2.09	.046	[-0.56, -0.01]

A moderation analysis was conducted to examine the impact of SN on BI, with UA as the moderating variable. The model explained a significant portion of the variance in BI (R = .55, R^2 = .30, F(3, 28) = 4.07, p = .016), accounting for approximately 30.35% of the total variance.

The test of the highest-order unconditional interaction between SN and UA revealed a significant interaction effect (ΔR^2 = .1089, F(1, 28) = 4.376, p = .0456), indicating that UA significantly moderates the relationship between SN and BI.

The direct effect of SN on BI was not statistically significant (b = 0.24, p = .108), as the confidence interval [-0.06, 0.53] included zero. However, UA had a significant negative main effect on BI (b = -0.63, p = .012), with a confidence interval of [-1.11, -0.15], suggesting that higher levels of UA are associated with lower BI.

The conditional effects of SN at different levels of UA were also examined. For individuals with low UA (−0.87), the effect of SN on BI was significant (b = 0.48, p = .012), with a confidence interval of [0.11, 0.85]. However, at average levels of UA (0.00), the effect was not significant, b = 0.24, p = .108, CI [-0.06, 0.53]. For individuals with high UA (+0.87), the effect of SN on BI was close to zero and not significant, b = -0.00, p = .967, CI [-0.40, 0.38].

These findings indicate that the positive relationship between SN and BI is strongest at lower levels of UA, and the effect diminishes as UA.

3.4. Relationships Between Uncertainty Avoidance, Perceived Substitution Crisis, and Clinicians' Perceived Usefulness of AI (H3 and H4)

This section presents the results of a linear regression analysis conducted to test two key hypotheses related to clinicians' perceptions of the substitution crisis due to AI. The first hypothesis (H3) posits that UA is positively correlated with PSC, suggesting that clinicians with higher levels of UA are more likely to perceive a greater threat of being replaced by AI. The second hypothesis (H4) proposes that there is an inverse relationship between clinicians' PU of AI and their PSC, indicating that those who view AI as useful are less likely to feel threatened by its potential to replace them.

To test these hypotheses, PROCESS macro Model 1 (Hayes, 2017) was employed. Bootstrapping with 5,000 resamples was applied to estimate the indirect effects, providing bias-corrected confidence intervals to assess the significance of the mediated pathways.

Table 5

Regression Analysis

	Perceived Substitution Crisis				
	b	se	t	p	CI
Uncertainty Avoidance	.46	.24	1.90	.067	[−0.03, 0.94]
Perceived Usefulness	-.68	.17	-3.93	<.001	[−1.03, −0.33]

The overall model was significant, explaining a substantial portion of the variance in PSC, $R^2 = .46$, $F\ (2, 29) = 12.50$, $p < .001$. This indicates that 46.3% of the variability in PSC can be explained by the combination of UA and PU of AI.

The Table 5 provides further information into the individual contributions of each predictor. PU of AI had a significant negative relationship with PSC (b = -0.68, t = -3.93, $p <$ .001). This supports H4, indicating that clinicians who perceive AI as more useful are less likely to feel threatened by a substitution crisis. The negative Beta coefficient shows that higher PU of AI is associated with lower levels of PSC.

UC was positively related to PSC, although this effect was marginally non-significant at the conventional level (*b* = 0.46, t = 1.90, *p* = .067). This suggests partial support for H3, as there is a positive trend between UA and PSC, but the effect did not reach statistical significance at the 95% confidence level.

In summary, the analysis revealed a strong, statistically significant inverse relationship between PU of AI and PSC, supporting H4. While UA showed a positive trend in relation to PSC, the effect was only marginally significant, not supporting H3.

3.5. Moderating Role of Individualism/Collectivism in the Relationship Perceived Usefulness and Behavioral Intention (H5)

A moderation analysis was conducted using PROCESS macro Model 1 to examine the moderating role of IC in the relationship between PU and BI.

To examine the hypothesis, PROCESS macro Model 1 (Hayes, 2017) was also employed. Bootstrapping with 5,000 resamples was applied to estimate the indirect effects, providing bias-corrected confidence intervals to assess the significance of the mediated pathways.

Table 6

Moderation analysis

	Behavioral Intention				
	b	se	t	p	CI
Perceived Usefulness (PU)	.80	.10	7.70	<.001	[0.587, 1.013]
Individualism/Collectivism (IC)	.12	.08	1.38	.179	[-0.058, 0.298]
PU*IC	-.05	.06	-.79	.435	[−0.18, 0.08]

The overall model was significant, indicating that the predictors explained a substantial portion of the variance in BI, R = .88, R^2 = .78, F(3, 28) = 32.95, $p < .001$). This suggests that approximately 77.93% of the variability in BI can be accounted for by the combination of PU, IC, and their interaction.

The coefficients for the regression analysis are presented in Table 6. PU had a significant positive effect on BI (b = 0.80, t = 7.70, $p < .001$), suggesting that higher perceptions of usefulness lead to greater behavioral intention. The effect of IC was not statistically significant (b = 0.12, t = 1.38, p = .179), indicating that this variable does not significantly impact BI.

The interaction between PU and IC was also non-significant (b = -0.05, t = -0.79, p = .435), suggesting that IC does not significantly moderate the relationship between PU and BI. The test for the highest-order unconditional interaction showed a negligible change in R^2 due to the interaction term (ΔR^2 = .01, F (1, 28) = 0.63, p = .435). This further supports the conclusion that IC does not significantly moderate the relationshi*p* between PU and BI in this analysis.

3.6. Moderating Role of Individualism and Collectivism in the Relationshi*p* Between Subjective Norm and Behavioral Intention (H6)

A moderation analysis was conducted using PROCESS macro Model 1 to test the hypothesis that IC moderates the relationship between SN and BI (H6).

To test hypothesis 6, PROCESS macro Model 1 (Hayes, 2017) was utilized. Bootstrapping with 5,000 resamples was applied to estimate the indirect effects, providing bias-corrected confidence intervals to assess the significance of the mediated pathways.

Table 7

Moderation analysis

	Behavioral Intention				
	b	*se*	*t*	*p*	*CI*
Subjective Norms (SN)	.12	.15	.80	.428	[-0.19, 0.43]
Individualism/Collectivism (IC)	.25	.15	1.62	.116	[-0.07, 0.57]
SN*IC	-.22	.10	-2.18	.038	[-0.43, -0.01]

The overall regression model was significant, with a substantial portion of the variance in BI explained by the predictors, R^2 = .29, F(3, 28) = 3.82, p = .021. This indicates that approximately 29.04% of the variance in BI can be attributed to the combination of PU, IC, and their interaction.

The coefficients Table 7 presents the individual effects of the predictors. SN had a positive but non-significant effect on BI (b = 0.12, t = 0.80, p = .428), suggesting that SN alone does not significantly predict BI. IC showed a positive but non-significant relationship with BI, b = 0.25, t = 1.62, p = .116.

The interaction term was significant, b = -0.22, t = -2.18, p = .038, indicating that the effect of PU on BI is moderated by IC.

The tests of highest order unconditional interaction revealed that the interaction between PU and IC was significant, with a change in R^2 of .12 (F(1, 28) = 4.75, p = .038. This suggests that IC significantly influences the relationship between SN and BI. The conditional effects of SN at different values of IC reveal that, at lower levels of IC (IC = -1.35), the effect of SN on BI was significant (Effect = 0.42, t = 2.21, p = .036), with a confidence interval of [0.03, 0.81]. At average levels of IC (IC = 0.00), the effect was non-significant (Effect = 0.12, t = 0.80, p = .428), as well as at higher levels of IC (IC = 1.35), Effect = -0.17, t = -0.78, p = .439.

In summary, the results provide support for H6, demonstrating that IC moderates the relationship between PU and BI, with significant effects observed at lower levels of IC.

CHAPTER 4

Discussion

This study aimed to examine how cultural and psychological factors affect the adoption of Artificial Intelligence AI-CDSS by healthcare professionals in Switzerland and Portugal. Specifically, it explored the role of cultural values—such as uncertainty avoidance and individualism versus collectivism—in shaping behavioral intentions to adopt AI-CDSS. The study also investigated how subjective norms and concerns about the "substitution crisis" (the fear that AI may replace human clinicians) interact with these cultural dimensions to influence adoption decisions.

Contrary to the expectation outlined in Hypothesis 1, subjective norms didn’t have a significant direct effect on behavioral intention to adopt AI-CDSS. This means that subjective norms didn’t predict the decision to adopt, suggesting that social pressures from peers or authority figures alone may not be strong drivers of AI-CDSS adoption in healthcare settings. These findings run contrary to expectations by Venkatesh and Davis (2000) in their TAM2, in which subjective norms were said to be a driver of technology adoption, mainly in organizational contexts where social conformity is at its strongest.

Supporting Hypothesis 2, uncertainty avoidance was found to significantly moderate the relationship between subjective norms and behavioral intention to adopt AI-CDSS. For individuals with lower levels of uncertainty avoidance, subjective norms positively influenced their intention to adopt AI-CDSS, indicating that individuals who are more open to ambiguity and change respond more to social influence when deciding to adopt new technologies. This finding is consistent with Hofstede's (2001) framework, which describes how lower uncertainty avoidance cultures are more adaptable and accepting of innovations, thus more likely to be influenced by peers when considering new technologies. Interestingly, his outcome differs from the findings of Hwang and Leet (2012), who reported that Uncertainty Avoidance significantly influences the relationship between subjective norms and trust dimensions (integrity and ability) rather than directly on behavioral intention.

In contrast, for individuals with higher uncertainty avoidance, the influence of subjective norms on adoption intentions was non-significant. Healthcare professionals with a stronger preference for stability and predictability appear less responsive to social influences, possibly due to their concerns about the potential risks and uncertainties associated with AI technology. Additionally, the study found that higher uncertainty avoidance generally corresponded with lower behavioral intention to adopt AI-CDSS, suggesting that those with higher uncertainty avoidance may require greater assurances regarding the safety, reliability, and predictability of AI-CDSS to consider adoption.

Hypotheses 3 and 4 explored the relationship between uncertainty avoidance, perceived substitution crisis, and perceived usefulness of AI. Hypothesis 3 posited a positive correlation between uncertainty avoidance and perceived substitution crisis, while Hypothesis 4 expected an inverse relationship between perceived usefulness and perceived substitution crisis.

Findings supported Hypothesis 4, as higher perceived usefulness of AI was associated with low scores of perceived substitution crisis. This result suggests that when individuals perceive AI as more useful and beneficial in their tasks or professional settings, they are less likely to experience feelings of insecurity or crisis related to the potential of being replaced by AI technologies. The inverse relationship may imply that recognizing the value AI adds to their roles might foster a sense of complementarity rather than competition, mitigating fears of redundancy or obsolescence.

Although uncertainty avoidance was positively associated with perceived substitution crisis (H3), this effect was only marginally significant, providing partial support for Hypothesis 3. This marginal significance may indicate a complex relationship in high perceived substitution crisis contexts. Specifically, Tran et al. (2021) noted that no associations were found between perceived substitution crisis and behavioral intentions to use AI. These findings suggest that while individuals in high PSC cultures may perceive potential threats from substitution, these perceptions do not necessarily influence their intentions or behaviors regarding technology use.

Hypothesis 5 proposed that individualism versus collectivism would moderate the influence of subjective norms on behavioral intention. The analysis supported it, demonstrating that individualism/collectivism moderates the effect of subjective norms on behavioral intention, particularly in collectivist contexts. This result aligns with Hofstede's framework, which highlights that individualistic cultures prioritize personal motivations and autonomy, making them less influenced by external social pressures when forming intentions (Hofstede, 2001). In contrast, collectivist cultures place a stronger emphasis on group identity and social cohesion, making subjective norms more significant in shaping behavioral intentions. Hofstede's findings further show that individualism/collectivism is a strong predictor of the adoption and integration of communication technologies even when economic factors like GNP per capita are controlled. This demonstrates that cultural dimensions, particularly collectivism, amplify the influence of social expectations on individual behavior, thereby moderating the effect of subjective norms on behavioral intentions (Hofstede, 2001, pp. 68-71).

Previous research by Srite and Karahanna (2006) highlights that collectivist individuals have a more developed "collective self," leading them to conform more readily to group norms. This behavior is driven by a strong desire for social harmony and the avoidance of actions that may be perceived as deviant.

In testing Hypothesis 6, which examined whether individualism versus collectivism moderates the relationship between perceived usefulness and behavioral intention, results showed no significant moderation effect. This finding suggests that cultural orientation (whether individualistic or collectivist) does not impact the translation of perceived usefulness into the intention to adopt AI-based Clinical Decision Support Systems. These results are consistent with those reported by Srite and Karahanna (2006), who also found that individualism/collectivism did not significantly moderate the relationship between subjective norms and behavioral intention. The lack of significance may be attributed to the measure of subjective norms, which included both inner-circle (e.g., family and friends) and outer-circle (e.g., professors) influences. In collectivist cultures, individuals are generally more influenced by close social connections within their inner circle, suggesting that a focus on these relationships may be necessary to detect cultural moderation effects.

The study's findings provide evidence for enhancing traditional technology adoption models, such as the Technology Acceptance Model (TAM), by integrating cultural dimensions. The observed influence of cultural dimensions like uncertainty avoidance and individualism/collectivism suggests that these factors are critical to understanding behavioral intentions toward AI-CDSS adoption, particularly in culturally diverse healthcare settings. Thus, models like TAM might be adapted to include subjective norms, perceived substitution crisis, and cultural values to better predict AI adoption in healthcare contexts.

The results offer practical insights for healthcare policymakers and administrators. Training programs tailored to address uncertainty avoidance could mitigate resistance in high uncertainty avoidance contexts, while messaging that emphasizes group benefits and social support could be effective in collectivist environments. These strategies could improve AI-CDSS acceptance, especially in settings that prioritize stability and established norms.

The study concludes that cultural values, particularly uncertainty avoidance and individualism vs. collectivism, significantly shape healthcare professionals' intentions to adopt AI-CDSS. Those with lower uncertainty avoidance are more receptive to social influences, while those with higher uncertainty avoidance require stronger assurances about AI reliability, reflecting cautious attitudes toward new technologies. Contrary to the TAM2, subjective norms alone do not directly drive AI adoption but are more influential in collectivist cultures, where social expectations weigh more heavily. Concerns about AI replacing clinicians also impact adoption, especially among those with high uncertainty avoidance, though perceived usefulness of AI helps to mitigate these fears. These findings suggest that enhancing TAM with cultural factors, subjective norms, and concerns about job substitution would provide a more nuanced understanding of AI-CDSS adoption in culturally diverse healthcare contexts. In summary, AI-CDSS adoption is a complex interplay of psychological factors, cultural values, perceived utility, and concerns about job substitution, with cultural dimensions emerging as critical in shaping these dynamics in healthcare.

4.1. Limitations and Future Directions

This study has several limitations that should be considered when interpreting its findings. First, the relatively small sample size may limit the generalizability of results across other healthcare settings or cultural contexts. Additionally, there was a lack of access to AI-CDSS software among many participants, as AI-CDSS technology is not yet widely integrated into all hospitals or educational institutions. This limited exposure may have influenced participants' responses, particularly in terms of perceived usefulness and ease of use. Furthermore, reliance on self-reported data may introduce bias, as participants' attitudes could be affected by hypothetical perceptions rather than actual experiences with AI-CDSS technology.

Future research should consider longitudinal studies to observe changes over time in attitudes toward AI-CDSS adoption and investigate the impact of other cultural and psychological factors not addressed here, such as power distance or long-term orientation. Additionally, studies with samples drawn from healthcare institutions where AI-CDSS is fully integrated would provide more precise insights into actual usage behaviors and acceptance patterns among healthcare professionals.

4.2. Conclusion

This study highlights the significant role of cultural and psychological dimensions in shaping healthcare professionals' intentions to adopt AI-CDSS in Portugal and Switzerland healthcare context. By integrating subjective norms, uncertainty avoidance, and perceived usefulness into traditional technology adoption frameworks, this research provides a culturally informed perspective on AI integration in healthcare. The findings contribute to the growing body of literature on AI adoption and offer practical insights for fostering technology acceptance across diverse cultural settings, emphasizing the need for culturally adaptive AI implementation strategies in healthcare.

The study's findings suggest several practical implications for promoting AI-CDSS adoption in healthcare. First, communication strategies should be tailored to address cultural orientations: healthcare professionals with high uncertainty avoidance may need clear evidence of AI-CDSS safety and reliability, potentially through detailed case studies or endorsements from trusted sources. In contrast, professionals with lower uncertainty avoidance might respond better to social validation, such as testimonials from colleagues. Additionally, targeted training programs can help address fears regarding AI reliability and job replacement, particularly for those with higher uncertainty avoidance. By providing hands-on experience and emphasizing AI as a supportive tool rather than a replacement, organizations can build trust and confidence in the technology.

For collectivist cultures where subjective norms play a more significant role, leveraging peer influence and group-based endorsements could increase AI-CDSS adoption. Strategies such as team-based pilot programs and presentations by respected figures in healthcare can help align adoption with cultural values of group cohesion and shared decision-making. Emphasizing AI's utility and benefits, such as enhanced clinical decision-making and efficiency, can also alleviate fears of job substitution. Finally, healthcare institutions can benefit from adapting traditional technology adoption models to incorporate cultural dimensions, subjective norms, and substitution concerns, creating a more comprehensive, culturally sensitive approach to encourage adoption in diverse healthcare settings.

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Appendix A

Consent Form

Welcome and thank you for your interest in this research.

This study is part of a research project taking place at Iscte – Instituto Universitário de Lisboa and aims to investigate cultural influences on the adoption of Artificial Intelligence in the healthcare system. You will be asked to provide insights into your perceptions and experiences with AI technologies in healthcare settings. This involves completing the following survey. Your participation is expected to take approximately 10 minutes.

Participation is completely voluntary, and you may withdraw at any time without penalty. Your responses will be kept confidential and anonymous. Data will be used solely for research purposes, all obtained data are merely intended for statistical processing, and none of the answers will be analyzed or reported individually. At no point of the study will you be asked to identify yourself. There are minimal risks involved. Your participation will contribute valuable information to the field of healthcare technology.

By selecting "Agree", you acknowledge that you understand the study's purpose, your role, and rights as a participant, and agree to participate.

Agree ○

Dont Agree ○

Appendix B

Debriefing

The study is interested in exploring how cultural contexts influence the adoption of Artificial Intelligence (AI) in healthcare systems. Specifically, it aims to understand how cultural dimensions impact healthcare professionals' attitudes towards and acceptance of AI technologies, focusing on AI Clinical Decision Support Systems (AI-CDSS).

Clinical decision support software (CDSS) is a category of medical software aimed at improving patient care quality and safety by helping doctors make evidence-based decisions. CDSS combines patient information with a clinical knowledge base to provide treatment suggestions specific to each patient. Traditionally, CDSS relied on information from medical literature, using rules and conditions to tailor recommendations. Now, with advances in technology, a new kind of CDSS uses artificial intelligence (AI) and machine learning (ML) to offer clinical advice.

Appendix C

TAM constructs and Cultural Values scale by Metallo et al., (2022)

Behavioral intention (BI)

BI1. Assuming I have access to the system, I intend to use it.

BI2. Given that I have access to the system, I predict that I would use it.

Perceived Usefulness (PU)

PU1. Using the system WILL improve my performance in my job.

PU2. Using the system in my job WILL increase my productivity.

PU3. Using the system WILL enhance my effectiveness in my job.

PU4. I find the system to be useful in my job.

Perceived Ease of Use (PEOU)

PEOU1. My interaction with the system is clear and understandable.

PEOU2. Interacting with the system does not require a lot of my mental effort.

PEOU3. I find the system to be easy to use.

PEOU4. I find it easy to get the system to do what I want it to do.

Subjective Norm (SN)

SN1. People who influence my behavior think that I should use the system.

SN2. People who are important to me think

Individualism-collectivism (IC)

IC1. Being accepted as a member of a group is more important than having autonomy and independence.

IC2. Group success is more important than individual success.

IC3. Being loyal to a group is more important than individual gain.

IC4. Individual rewards are not as important as group welfare.

Uncertainty avoidance (UC)

UC1. Rules and regulations are important because they inform workers what the organization expects of them.

UC2. Order and structure are very important in a work environment.

UC3. It is better to have a bad situation that you know about, than to have an uncertain situation which might be better.

UC4. People should avoid making changes because things could get worse.

Long-short term (LT)

LT1. Respect for tradition is important for me.

LT2. I work hard for success in the future.

LT3. Traditional values are important for me.

LT4. I plan for the long term.

Power distance (PD)

PD1. Managers should make most decisions without consulting subordinates.

PD2. Manager should not ask subordinates for advice, because they might appear less powerful.

PD3. Decision making power should stay with top management in the organization and not delegate to lower-level employees.

PD4. Employees should not question their manager's decision.

Appendix D

Perceived substitution crisis Scale by Fan et al., (2020)

PSC1. I think that AI-CDSS will likely replace doctors in the future.

PSC2. I think using AI-CDSS for a long time would make doctors dependent on them.

PSC3. I think the rise and development of AI-CDSS would likely lead to unemployment of some doctors.

PSC4. I think using AI-CDSS for a long time would decrease doctors' own diagnosis ability.