French Patient Perception of the Use of AI Technologies in Primary Care Consultations

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Dissertation written under the supervision of Professor Peter V. Rajsingh and Professor Boris Duricin.

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Abstract

This study examined French patients' perception of the use of artificial intelligence (AI) technologies in primary care consultations, analyzing the factors that influence acceptance and resistance. In an environment such as healthcare where stakes are high and errors can lead to significant consequences, AI technologies must be carefully implemented. While they promise enhanced efficiency, more accurate diagnosis and reduced healthcare disparities, their successful adoption depends on patients' trust and willingness to accept such systems. Grounded in the Technology Acceptance Model (TAM), Unified Theory and Use of Technology (UTAUT), and risk-based theories, this research investigated how perceived risks and benefits, ethical concerns and sociodemographic factors shape patients attitudes toward AI technologies in primary care consultations.

A quantitative survey of 188 participants assessed perceptions across four different dimensions: (1) demographics and AI familiarity, (2) patient-doctor relationship, (3) perceived benefits of AI, and (4) concerns about risks and ethics. The exploratory factor analysis identified two key constructs: Acceptance measuring openness and Fear_Risk evaluating apprehension that significantly influenced trust toward AI usage for health diagnostics.

The results revealed that patients who viewed AI as beneficial for improving health diagnosis and reducing physicians' workload were more likely to accept its use, while those who fear technical errors and data misuse were more reluctant to its adoption. Notably, prior experience with AI tools did not prove significant correlation with higher acceptance, suggesting domain-specific trust barriers.

By prioritizing transparency, addressing ethical concerns through robust governance and design hybrid human-AI systems, stakeholders might foster greater adoption.

Keywords: artificial intelligence adoption, healthcare, French patients, patients' perception, technology acceptance, data privacy, primary care

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Sumário

Este estudo investigou a percepção de pacientes franceses sobre o uso da inteligência artificial (IA) em consultas de cuidados primários, analisando fatores que influenciam a aceitação e a resistência. No setor da saúde, onde os riscos são altos, a implementação da IA exige cautela. Apesar de prometer diagnósticos mais precisos, eficiência e redução de desigualdades, sua adoção depende da confiança dos pacientes.

Baseado no Modelo de Aceitação da Tecnologia (TAM), na Teoria Unificada de Aceitação e Uso da Tecnologia (UTAUT) e em teorias baseadas no risco, o estudo explorou como os riscos percebidos, preocupações éticas e fatores sociodemográficos moldam as atitudes dos pacientes.

Foi aplicado um questionário quantitativo a 188 participantes, abordando quatro dimensões: (1) perfil demográfico e familiaridade com IA, (2) relação médico-paciente, (3) benefícios percebidos da IA e (4) preocupações com riscos e ética. A análise fatorial identificou dois construtos principais: Aceitação (abertura à IA) e Medo_Risco (apreensão), que influenciaram a confiança dos pacientes no uso da IA para diagnósticos médicos.

Os resultados mostraram que pacientes que percebem benefícios na IA, como melhora no diagnóstico e alívio da carga médica, tendem a aceitá-la mais. Por outro lado, o medo de erros técnicos e mau uso de dados reduz essa aceitação. A experiência prévia com IA não foi significativamente associada à aceitação, indicando barreiras específicas na área da saúde.

Para promover a adoção, recomenda-se maior transparência, atenção às questões éticas e o desenvolvimento de sistemas híbridos humano-IA.

Palavras-chave: adoção de inteligência artificial, saúde, pacientes franceses, percepção dos pacientes, aceitação tecnológica, privacidade de dados, cuidados primários

Título: Percepção dos Pacientes Franceses sobre o Uso de Tecnologias de IA em Consultas de Cuidados Primários

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AI tools were used for language refinement and coding during the preparation of this paper. Critical-thinking, data analysis and conceptual development remain the sole responsibility of the author.

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List of Abbreviations

AI: Artificial Intelligence

CAQES: Contrat d'Amélioration de la Qualité et d'Efficience des Soins

DOI : Diffusion of Innovation

EHRs: Electronic Health Records

GP: General Practitioner

ICT: Information and Communication Technology

LLMs: Large Language Models

MANOVA: Multivariate Analysis of Variance

ML: Machine Learning

UTAUT: Unified Theory of Acceptance and Use of Technology

WHO: World Health Organization

1. Introduction

Artificial Intelligence (AI) is rapidly transforming the healthcare systems, offering new opportunities of enhanced diagnostic accuracy, improved efficiency, and increased accessibility to medical care. As AI technologies such as Machine Learning (ML) and Large Language Models (LLMs) become increasingly capable, their potential in augmenting clinical decision-making is expanding rapidly. In a high stakes environment such as healthcare where the demand for accuracy, efficiency and equity is constant (Hoff & Bashir, 2015), ensuring the integration of these dimensions while implementing AI is paramount.

In France, where patients experience dissatisfaction with primary care consultations such as physician shortages (European Commission, 2023), lack of patient-centered relationship (WONCA Europe, 2023) and discrimination (Huteau & Legros, 2018), AI presents a potential solution to alleviate these challenges. Although AI implementation is increasingly evolving from diagnostic algorithm to virtual assistants (Galland et al., 2024; Auriacombe et al., 2021), little is known about how French patients view these technologies in the context of their routine primary care.

The successful integration of AI systems comes not only with technical feasibility, but also with patient acceptance and trust. This study investigated French citizens', or individuals' residing in France perception of AI in primary care consultations. Primary care is defined as the initial point of contact between a patient and a general practitioner, focusing on assessing the patient's condition and establishing a diagnosis (Torres et al., 2018). This process plays a crucial role in shaping overall health outcomes and patient satisfaction (World Health Organization, 1988). As such, uncovering patient attitudes toward AI is essential for designing a human-centric approach that meets user's needs and expectations.

This research was built upon established theoretical frameworks such as the Technology Acceptance Model (TAM) (Davis, 1985), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), the Diffusion of Innovation (DOI) (Rogers, 1986) and risk-based theories (Mitchell, 1999; Richardson et al., 2021; Tran et al., 2019). These models contributed to the development of our hypotheses which aimed to understand how perceived usefulness, ease of use, social influences and perceived risk impact patients' willingness to trust AI healthcare solutions.

Through a quantitative survey, this study evaluated different dimensions, namely patients' demographics and AI familiarity, relationship with doctors, perceived benefits of AI use, concerns and fears, and finally trust in AI. By analyzing responses from **188** participants, we addressed the following research questions:

RQ1: How do French patients perceive AI technologies in primary care consultations?
RQ2: Which underlying factors influence patients' trust in AI-based healthcare diagnoses?

The findings provided empirical evidence on patient attitudes in France by uncovering underlying factors and patterns influencing their perception. In doing so, this study not only contributed to the academic discourse on AI, but provided insights for policymakers, healthcare providers, and technology developers aiming to create AI-centered medical solutions.

As France invests in its "Stratégie d'Accélération Numérique" (Gouvernement, 2021) to become a leader in digital health innovations by 2030, this study represents a key exploration of the patients' perspective today. The overreaching goal of this thesis was to emphasize a fundamental truth: AI integration in healthcare can only be successful if it is designed in ways that earn the trust of individuals it is intended to serve. in shaping overall health outcomes and patient satisfaction (Rodriguez Torres et al., 2

2. Literature Review

2.1. Medical Consultations and Digital Transformation

Primary care consultations define the doctor-patient relationship and represent a process where a specialized physician provides physical, emotional, and psychological support to patients (Torres et al., 2018). During consultations, the doctor follows a standard protocol to assess vital signs and understand specific ailments such as pain or discomfort, and provide a concise diagnosis followed by a solution to address these needs (Torres et al., 2018). The ultimate goal of medical consultations is improvement in the health and well-being of patients, as well as their satisfaction with the service provided based on quality, efficiency and cost-effectiveness (World Health Organization, 1988).

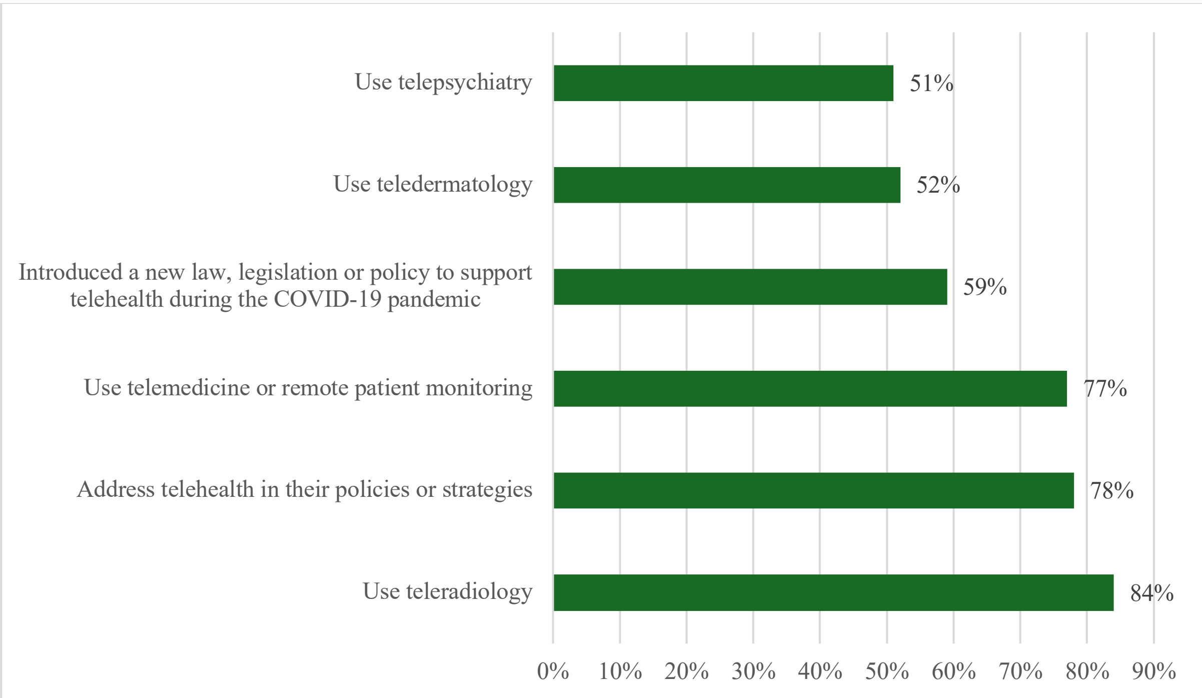
With technological advancements rapidly evolving and needs changing, including the imperative to reduce costs and inefficiencies of healthcare delivery, medical consultations are evolving from the traditional mode of face-to-face consultations. This is evident in various ways to address factors such as accessibility, time efficiency, sense of emergency, risk of infections, and convenience, benefiting both patients and practitioners. (Atherton, Brant, Ziebland, et al., 2018). Digital transformation is a classic disruptor*,* as seen across a variety of new technologies such as internet of things, blockchain, machine learning and artificial intelligence, impacting healthcare services (Baudier et al., 2023). In medicine, emerging innovations such as telemedicine and e-health are shaping the way medical consultations are delivered, ultimately shifting the focus from disease to the physical and mental well-being of patients (Baudier et al., 2023).

2.1.1. Telemedicine

Telehealth is digital health services that include telemedicine or remote patient monitoring, telepsychiatry, teleradiology, telepathology and teledermatology (World Health Organization, (2023). Additionally, it *"supports and promotes (...) health-related education, public health and health administration"* (CDC, 2024). Telemedicine is a part of telehealth and is defined as a healthcare service where patient and physicians are separate by a distance (Commission of the European Communities, 2008), where the patient transmits information through verbal communication, or monitoring equipment (World Health Organization, 2023). Since Covid-

19, adoption of technology in medical consultations has intensified. In the United States, a national study including 36 million privately insured individuals reported a 766% increase in telemedicine between March and June 2020, with 23.6% of telemedicine consultations compared to the same period in 2019, where only 0.3% of telemedicine consultations were performed (Weiner et al., 2021). In Europe, on the other hand, telemedicine was adopted in 2022 in 51 member states (WHO, 2023). As illustrated in Figure 1, among telehealth services, 77% of member states adopted telemedicine or remote patient monitoring.

Figure 1: Share of 51 European countries using telehealth services or policies in 2022



Source: (World Health Organization, 2023)

As a means of primary care, chronic disease monitoring or post-surgery follow-up, telemedicine offers a range of benefits, disrupting the healthcare industry. Since Covid-19, its use has grown tremendously, due to efficiency, accessibility, flexibility, and patient satisfaction (Ezeamii et al., 2024; Palozzi et al., 2020; Westwood, 2021). In fact, 186 patients with chronic conditions such as diabetes, cancer, multiple sclerosis and mental health problems found that telehealth was a key tool for improving health outcomes and reducing costs associated with traveling (Ezeamii et al., 2024). In addition, telemedicine helps minority patients, reducing stigma and discrimination (Ezeamii et al., 2024).

Moreover, telemedicine can take various forms, from fully digital to hybrid model, which alternates both in-person consultations and online consultations. This demonstrates its flexibility in adapting to specific healthcare specialties such as post-surgery follow-up, chronic disease monitoring, psychotherapy or primary care, some of which require physical examination and diagnostic testing. (Westwood, 2021). Finally, by providing access to healthcare for people living in rural areas, telemedicine as an innovation contributes to the achievement of the UN Sustainable Development Goals 3 and 10, namely good health and well-being and reduced inequalities. (Palozzi et al., 2020).

2.1.2. Electronic Health Records

According to the International Organization for Standardization, Electronic Health Records (EHRs) are defined as the storage of patient's health data on a secure, accessible and manageable digital database. Its purpose is to provide access, monitor, and ensure visibility on the patient's health status (Hayrinen et al., 2008). Patient health records may include past and current treatments, allergies, medications, laboratory tests, surgical history or radiology images (World Health Organization, 2016).

The number of countries where primary care physicians use EHR systems has grown from 10 countries among 22 in 2012, to 18 countries among 27 in 2021 (Slawomirski, et al., 2023). A report conducted by the World Health Organization (2023) in Europe shows that among 52 member states of the organization, 45 have an EHR system within their nation. Research conducted in 8 low-income countries located in Africa revealed that countries such as Ethiopia, Uganda and Gabon are still at pilot stage and thus not yet fully implemented. However, 75% of healthcare professionals express optimism about EHRs improving patients' health, which demonstrates a willingness to adopt these systems (Woldemariam & Jimma, 2023).

EHRs transfer paper documentation into a digital database, improving patient safety, procedural efficiency, and treatment efficacy. Patient safety is related to minimizing medical errors as well as the protection of data and privacy (Menachemi & Collum, 2011). A systematic review on the impact of EHRs on healthcare quality found out that medication errors were 54% lower when healthcare institutions used EHR systems (Campanella et al., 2016). Procedure efficiency includes reducing time-consuming tasks, such as minimizing indirect care activities like documentation (Bouh et al., 2024) as well as the avoidance of unnecessary redundant diagnostics such as laboratory tests and imagery (Menachemi & Collum, 2011). Additionally, treatment effectiveness refers to the quality of care given to patients. EHRs can help in providing such quality by framing scientifically based guidelines for healthcare providers to follow (Menachemi & Collum, 2011). Finally, another benefit important to mention is EHRs in countries impacted by humanitarian crises due to conflicts or wars. With rapid turnover of doctors, such systems help in managing continuity of care for patients receiving assistance across different clinicians, as well as preventing the spread of infectious diseases by providing a source of data for public health surveillance (Draugelis et al., 2025).

Although EHRs offer numerous benefits, adoption is often hindered by high costs, inadequate infrastructure, shortage of skilled professionals, and resistance to change. In fact, 19 member states of the World Health Organization outlined that an insufficient funding can represent an obstacle in the implementation of EHRs (World Health Organization, 2023). Indeed, national systems require an initial high investment as well as a long-term commitment for its success (World Health Organization, 2016). Additionally, limited access to internet connectivity and unreliable electricity in rural areas represent technical infrastructure barriers slowing down the full implementation of EHRs (Mwogosi & Kibusi, 2024).

Reducing the cost of internet connectivity and cloud storage will be key for overcoming this barrier (World Health Organization, 2016). Research carried out by Perera et al. (2011) highlights the security and privacy issues as an obstacle. Indeed, among 490 patients and 23 physicians interviewed, about half of the respondents expressed concerns about the security of the data due to its transmission through the internet. Finally, resistance to change is evident due to the lack of skilled information and communication technology, necessary for implementing and sustaining EHRs systems (Mwogosi & Kibusi, 2024).

2.1.3. Wearable Technologies

Wearable devices are technologies that monitor health-related data over time, such as physical activity, vital signs, and heart activity. They track and record information such as body temperature, heart rate, sleep cycles, stress level, steps taken, workout length, and sedentary length (Liao et al., 2019). These devices are intended to be worn at home, and benefit to individuals living in rural areas or with limited access to resources, as well as individuals who need continuous health monitoring (Dunn et al., 2018).

Data collected through wearable devices is generally stored and accessed through mobile apps, web-based wearable platforms, or directly from wearable companies (Hsiao et al., 2023). Big data retrieved from such technologies allow healthcare professionals to personalize their treatment ultimately leading to better preventive care (Kristoffersson & Lindén, 2020). Additionally, artificial intelligence and machine learning included in some wearable devices help in predicting diseases earlier than traditional methods. For instance, a smartwatch with an electrocardiogram tested on 14,000 participants was able to detect atrial fibrillation with 97% accuracy (Dunn et al., 2018). Finally, another benefit of wearable devices is the reduction of unnecessary volume in hospitals, which ultimately reduces costs and stress for healthcare professionals, as well as unnecessary transport by individuals, which is costly and time consuming (Iqbal et al., 2021).

2.2 Medical Consultations in France

In general, French individuals express satisfaction with the healthcare system in France. In fact, a survey of hospitalized patients highlighted a score of 72.7 out of 100 for satisfaction with care management, reception, discharge organization as well as room and meals (Haute Autorité de Santé, 2016). Additionally, France had the second highest health expenditures in the European Union, reaching 313 billion euros in 2022 which showcases a high level of governmental support in healthcare delivery (Eurostat, 2024b). In terms of medical consultations per individual, France only ranked in the lower-middle range among EU countries in 2022 (Eurostat, 2024a). This low number could highlight barriers to access, doctor shortage, financial limitations and more. The following section will take an in-depth look at the organization of medical consultations in France, highlighting current challenges and areas of dissatisfaction.

2.2.1. Regulation of Medical Consultations in France

In France, medical consultations follow strict regulations to ensure quality, ethics and data privacy. A code of ethic elaborated by the French government aims at providing a guideline for every physician to follow, when delivering healthcare services (Ordre National des Médecin, 2017). This protocol covers aspects such as quality of care as outlined in the articles 32 and 33 where physicians must rely on scientific knowledge and techniques, while ensuring they take sufficient time to establish an accurate diagnosis. Additionally, ethical principles are emphasized in articles 2 and 7, which prohibit discriminatory practices violating human rights and dignity, even after the patient's death. Finally, data privacy and confidentiality are aspects protected by the code of conduct and can be found in articles 4, 45 and 72. Additionally, the General Data Protection Regulation (GDPR) which applies across the European Union, protects personal data. Health institutions, including private cabinets of physicians handling patients' data residing in France, must comply to the GDPR (European Data Protection Board, 2019).

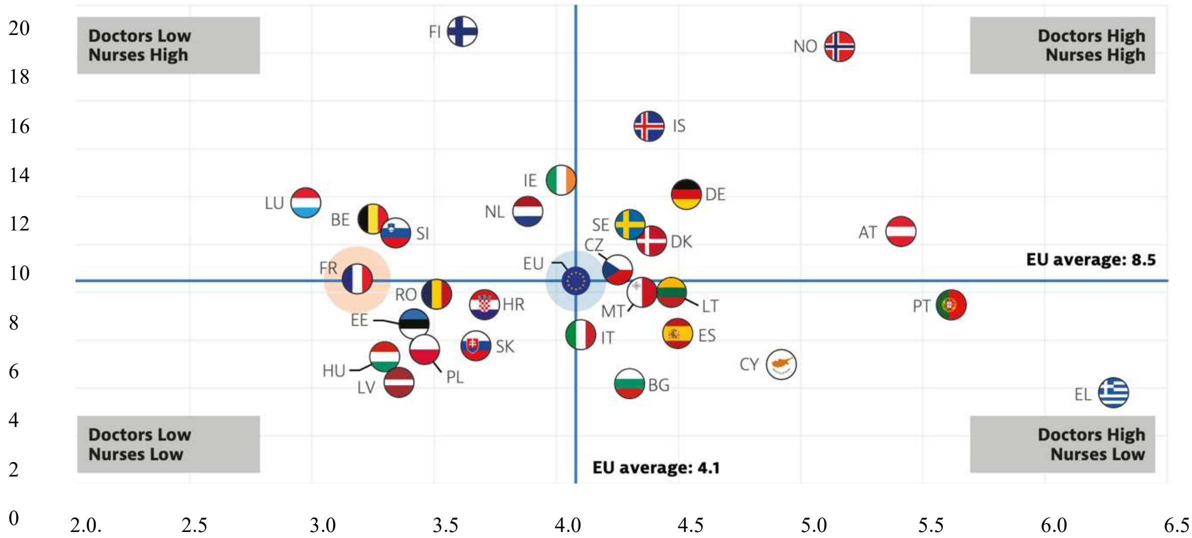
The World Organization of Family Doctors (WONCA) in the European region developed standards that ensure high quality during medical consultations. In fact, care should be patient-centered, therefore providing a holistic approach to the psychological, physical, and environmental aspects, while maintaining an effective communication for better understanding (WONCA Europe, 2023). Additionally, the World Health Organization's Regional Committee for Europe, developed a report outlining the process to ensure quality of health services among the member states. In fact, to ensure good quality, health services should follow three aspects: the process of care, the structure of care, and finally, the result of care. Moreover, any process of care would be only considered of high quality if it leads to a desired outcome (World Health Organization, 1988). However, even though health services follow strict European regulations, different factors still affect the quality, delivery and patients' satisfaction of medical consultations.

2.2.2. Factors contributing to dissatisfaction with medical consultations in France

Shortage of GPs and unequal distribution

Many factors contribute to French individuals' dissatisfaction with medical consultations. First, a lack of General Practitioners (GPs) nation-wide causes accessibility issues. This is shown in , where the number of practicing doctors per 1000 inhabitants in France (3.1) is below the EU average (4.1), while more elderly people in France suffer from chronic diseases than the EU average (46% of men in France compared to 32% in the EU and 46% of women in France compared to 40% in the EU) (European Commission, 2023).

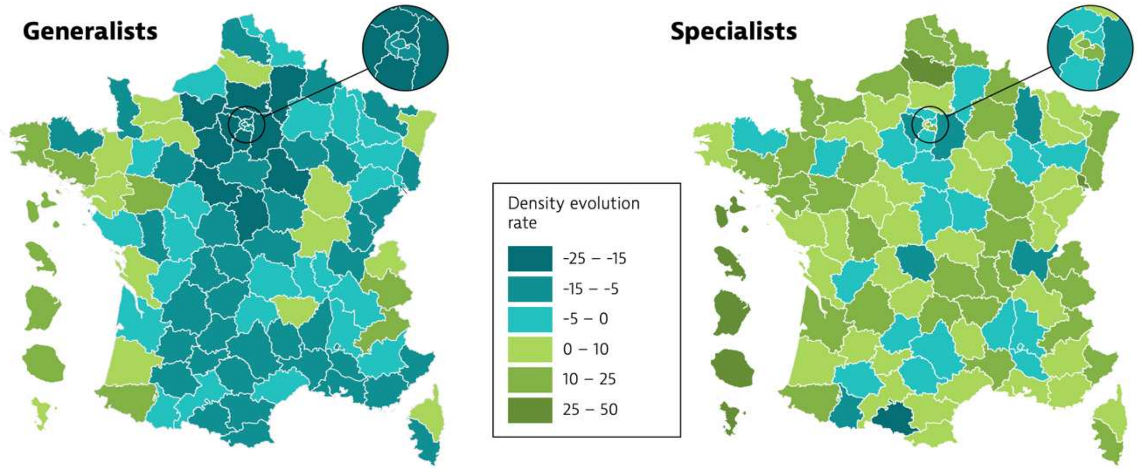
Figure 2: Number of practicing doctors and nurses per 1000 population in France compared to the EU average



Source: (European Commission, 2023)

Figure 3 shows that between 2018 and 2022, the number of generalists doctors across several French regions has drastically decreased, while the number of specialists increased. This is mainly around the capital region of Paris but affects the whole national territory. In total, 79 departments out of 96 recorded a decrease in general practitioners (Ministère des Solidarités, 2023). This gap between GPs and specialists can be explained by the disinterest shown by medical students in choosing general practice over specializing. A national survey made on 1870 French medical students in 2009 showed that only a quarter of the respondents (n= 432) were interested in pursuing a career as general practitioners (Lefèvre et al., 2010). Another factor contributing to this gap is the approaching retirement of current GPs, who are not being sufficiently replaced, as previously mentioned (DREES, 2021). This has led to increased divergence in access to care across regions. Indeed, the proportion individuals living in regions where GP density is more than 20% below the national average rose from just 1% in 2012 to 4% by 2021, while those in regions more than 10% below average rose from 11% to 28% over the same reference period (Anguis et al., 2021).

Figure 3: Density of General Practitioners and Specialists accross France between 2012 and 2022



Source: (European Commission, 2023)

Discrimination

Another factor contributing to the dissatisfaction with medical consultations is the discrimination of certain groups in access to health services. A study carried out in 2022 aimed to measure the level of refusal by general practitioners to treat people benefiting from the "Aide Médicale d'Etat", a governmental program providing access to care to socially disadvantaged individuals. 14% to 36% of people living in precarious situations have less chances to obtain a medical appointment with a GP (Le Rolland et al., 2023). Research conducted between 2008 and 2009 assessed discrimination in healthcare with 21,761 individuals-based data on factors of origin, gender, and religion. Inter alia, it showed that Muslim first-generation women from Africa reported a higher rate of discrimination (4.7% compared to 3.0% for men) (Huteau & Legros, 2018).

Lack of Quality

Finally, quality is another dimension affecting the satisfaction of primary care among French individuals. A survey aiming at assessing 4,078 French elderly's experience with primary care highlighted a lack of patient-centered approach during medical consultations. Over 40% expressed clear dissatisfaction with their practitioners regarding additional support such as financial, human, social, and psychological. In addition, one in 4 patients said their caregiver did not receive proper information from the doctor to support the patient at home. Finally, around 20% of respondents felt that no one was available when their usual doctor was absent and they did not know where to seek medical help (Angibaud et al., 2025).

This lack of quality and efficiency could be linked to the fact that many health institutions still do not comply with the “Contrat d’Amélioration de la Qualité et d’Efficience des Soins” (CAQES), a contract aiming at improving the quality and efficiency of care. In fact, only 5 out of 13 French regions possess the CAQES. Additionally, French overseas departments such as Guyane and Mayotte neither implemented nor complied with the CAQES (Ministère des Solidarités, 2023).

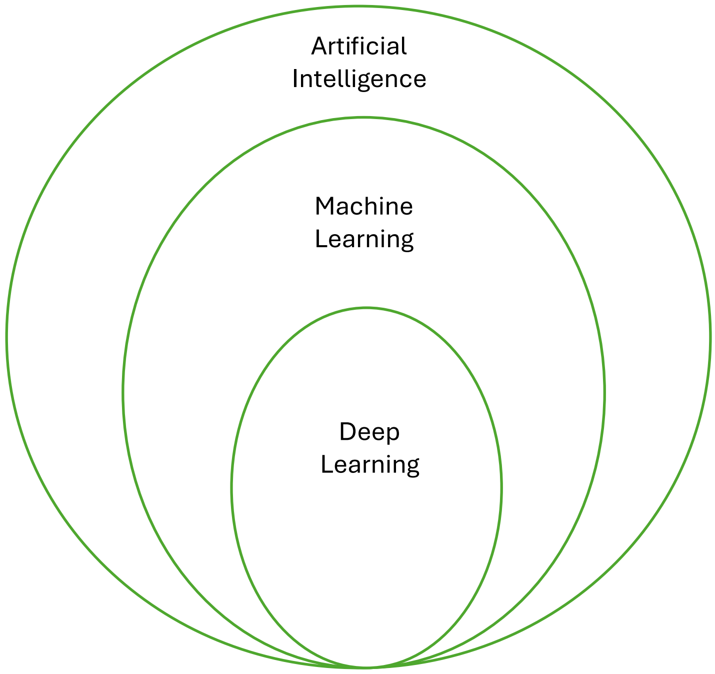
2.3. Introduction to AI

Artificial Intelligence (AI) is defined as a technology that enables machines to mimic human intelligence by executing capabilities such as conversating, making decisions and reasoning (De Spiegeleire et al., 2017). The definition of AI was officially introduced by McCarthy during the 1956 Dartmouth Conference, laying the foundation for AI as a recognized field of study, capable of replicating human intelligence (McCarthy, 2007). AI is not a recent concept, as it can be traced back to the early twentieth century. Alan Turing first introduced the conceptual foundation of AI in his paper “Computing Machinery and Intelligence” (1950), where he developed a test famously known as the “Turing Test”, to determine whether a machine could “think” by imitating a human conversation.

The history of AI followed different phases of growth called “springs” and “winters”. Indeed, despite the creation of the first chatbot, there was limited computer processing power, data storage capacity and network ability which led to the first setback in 1964. In 1980, AI experienced a rebound with the first “Expert System,” enabling seamless possibilities thanks to neural networks, optical character recognition (OCR) and speech recognition. From 2011 until today, AI has seen tremendous improvements in its predictive algorithm capabilities. Accessibilities such as the extraction of data from open sources, affordable data storage, and cloud infrastructures, have enabled big data and machine learning (ML) to practice human cognitive functions such as recognizing patterns and faces, as well as conversating like humans (De Spiegeleire et al., 2017).

Deep learning (DL) is a subset of machine learning (IBM, 2023), and is defined as a *"computational system that learns for itself how to perform on a basis of very large sets of data"* (Dupre, 2021). DL uses the back propagation algorithm, first introduced by Rumelhart et al.(1986), enabling the deep neural networks to train the models by going from output to input, seamlessly adjusting the weights to correct the errors for better results (IBM, 2023). Figure 4 below summarizes the structure of AI and its subfields ML and DL.

Figure 4: Hierarchical structure of AI and its subsets.



Note: Adapted from IBM (2023)

In medicine, DL is being trained and tested to see if models could outperform traditional detection methods in terms of accuracy and speed. In fact, an Indian study of DL models trained on labeled X-ray images and demographic data, showed the model performed with an F-1 score of 0.907, demonstrating a high detection accuracy (Rahane et al., 2024). DL in medicine increases the precision and reliability of diagnoses and helps doctors choose the most appropriate treatment for patients, thereby improving prognoses (Morik et al., 2023). However, DL also faces challenges such as costs, data privacy, biased training datasets and the lack of expert-labeled data which can skew the results (Ching et al., 2018).

2.3.1. The use of Artificial Intelligence in France

In France, the government is trying to transition to a more curative, preventive and personalized healthcare approach. To achieve this, a strategy to accelerate digitization in healthcare "stratégie d'accélération santé numérique" has been implemented in 2024, aiming at positioning France as the leader in digital health innovation by 2030 (Ministère de l'Economie des Finances et de la Souveraineté Industrielle et Numérique, 2024). To make this goal achievable, the French government allocated a budget of 500 million € (Ministère Chargé de la Santé et de l'Accès aux Soins, 2025) to form healthcare professionals, accelerate research and support the development of AI technologies in the medical field (Gouvernement, 2021).

One prominent use is in image recognition, where AI refines digital impressions of the mouth by removing blurred or irrelevant elements. Additionally, ML and DL techniques are used to process large volumes of data from EHRs, aiming to predict the risk of disease development based on patients' systemic health data. This integration does not only save time for doctors, but also allows an early intervention and curated treatments (Ducret et al., 2022). Another example of the use of AI in healthcare is in oncology, which is the study and treatment of cancer. In the detection of breast cancer, DL algorithms are using classification methods based on tissue samples from cancer cells, to classify if patients' cells have a defect in DNA repair process. In this case, AI helps identify the most adequate treatment approach, based on whether the patient's cells present a defect in the DNA repair process or not (Lazard et al., 2023). A study conducted by Galland et al., (2024) evaluated if a physician assisted by a predictive AI technology could increase the accuracy in the diagnosis of rare diseases, compared to when the physician is alone. The results showed that the use of AI technology improved accuracy by 28.1%.

E-health which is defined as a "*set of technologies applied with the help of the internet, in which healthcare services are provided to improve quality of life and facilitate healthcare delivery*" (Da Fonseca et al., 2021), is strongly supported and encouraged by the French government, and a wide array of innovative technologies is being developed by French entrepreneurs in this field. In fact, some earned recognition during the fifth e-Health Talent Awards ceremony in December 2024 (Agence du Numérique en Santé, 2024). Examples include innovations in the social sector where "Animia," a digital application offers personalized activities that promote autonomy and social inclusion for individuals with disabilities or loss of independence thanks to AI (Agence du Numérique en Santé, 2024). In the field of mental health, "Kanopee" is a digital application launched in 2020 which uses a virtual avatar to provide early identification of risks of addictions, sleep disorders, and stress (Auriacombe et al., 2021). Since its launch, “Kanopee” is used by more than 60 000 users in France (Gouvernement Français, 2025). Regarding medical consultations, “Nabla” generates medical reports with the use of generative artificial intelligence, ultimately saving time for doctors and improving the relationship with their patients (Nabla, 2025). In addition, by enabling automatic medical notes, “Nabla” prevents the risk of physicians’ burnout through the reduction of cognitive load during each patient visit (Misurac et al., 2024).

Finally, the big digital health platform Doctolib has developed its own medical assistance powered by AI, aiming at taking notes during consultations and prepare tasks associated with patients’ requests, making the communication between doctors and patients more humane (Nacim, 2024). These examples are driving digitalization and highlight the importance of innovation in the French healthcare sector. However, since AI systems are classified as high-risk in healthcare meaning *“it can pose a significant risk of harm to the health, safety and fundamental rights of natural persons”* (EU Artificial Inteligence Act, 2024), their use in this field presents numerous challenges and considerations, which will be explored in the next section.

2.3.2. Challenges and Barriers to Adoption of AI in Healthcare

Ethical considerations

Although AI systems in healthcare are representing a new opportunity, they raise ethical considerations. These issues include concerns about lack of shared decision-making, communication, fairness, and data privacy (Karimian et al., 2022).

In fact, AI systems can hinder the principle of “human autonomy”, which is described as a right to self-determination, self-rule and self-governance (Laitinen & Sahlgren, 2021). Autonomy is also considered as a valuable component of human dignity and well-being that must be respected. Recommendation and personalization systems could lead to direct interference and deception, or in worst cases manipulative and coercive influence. (Laitinen & Sahlgren, 2021). Examples in healthcare include lack of patient-centeredness and shared decision-making, as well as the possibility for individuals’ preferences to be ignored (Karimian et al., 2022).

The complexity of algorithms, illustrated by “black-box issues,” represents an obstacle for effective transparency in the functioning of AI systems. Lack of communication about the benefits and drawbacks of AI algorithms in healthcare could lead to misunderstandings and miscommunication between healthcare providers and patients (Karimian et al., 2022). However, explanation is not enough without the users’ full understanding of the system.

Limited data diversity during AI training process produce unconscious bias leading to unfair provision of care (Karimian et al., 2022), misdiagnoses, and lack of generalization (Norori et al., 2021). Regarding demographic discrimination, an example of sleep scoring showed erroneous results when algorithms tried to reveal sleep disorders for older patients because they were trained on young and healthy individuals. Ultimately, all of these issues stem from the lack of diversity in the data, which leads to algorithmic bias (Norori et al., 2021). In addition, inaccessibility to digital healthcare for some communities also leads to inequalities in technology adoption (Yao et al., 2022).

Key ethical concerns surrounding the use of AI in healthcare have not been comprehensively addressed. There is no widely accepted set of guidelines or framework to ensure the ethical development and deployment of AI-based decision support systems in healthcare. (Karimian et al., 2022)

Data privacy

Patient data privacy and security is a major concern in healthcare technologies. Privacy can be defined as the protection of one’s personal health information while security is considered as the protection from unauthorized access. These two dimensions must be in compliance with regulations, with authorization requirements in place for the use, processing and sharing of patient data, while at the same time ensuring that data is not misused for profit (Abouelmehdi et al., 2018). Currently, machine learning and convolutional neural networks technologies are owned by big private corporations such as Google, Microsoft, IBM, Amazon or Apple, which process patients’ data. Partnerships between these companies and public institutions for the implementation of ML have resulted in weak data privacy protection. For example, Google’s AI DeepMind, partnered with the Royal Free London NHS Foundation for ML to help manage kidney injuries. There were evident concerns over transparency, collection, and use of patient data, as well as data transfer issues about security and ownership of data moved from the UK to the US (Murdoch, 2021).

Different frameworks aim at regulating data privacy and security. In Europe, the GDPR aims to protect patients' past, present and future data, including physical and mental health information such as test results, treatments, physiological or biomedical status, regardless of which healthcare institution processes the information (doctor, hospital, medical device or laboratory). Additionally, articles 13 and 14 of the GDPR emphasize the information that must be given to the patient such as the purpose of the processing, their rights to access and withdraw, as well as the data retention period (European Parliament, 2016).

Responsibility

The question of responsibility for AI failure raises legal and ethical issues. AI tools still have limitations and can switch from being extremely intelligent to naïve (Naik et al., 2022). Currently, technologists, including developers, are not legally responsible. However, doctors and hospitals that use and follow AI recommendations bear the ultimate responsibility for any harm caused to patients. (Naik et al., 2022). Another view is that whenever doctors commit errors when using AI technologies, they will be held accountable, especially if they have received training. However, if the error is caused by the algorithm or the data used to train the model, the responsibility is assigned to the developers (Mennella et al., 2024). This showcases the complexity of assigning responsibility and accountability to the right entity, in case of erroneous results or harm to the patient.

ChatGPT, a large language model from OpenAI, has been widely used in radiology reporting, providing antimicrobial advice, improving clinical decision making, and automating discharge notes (Wang et al., 2023). In this case, healthcare professionals are responsible for validating or rejecting AI-generated advice based on clinical guidelines, as well as maintaining empathy and human connection with the patient. Nevertheless, developers need to ensure transparency and explainability regarding the limitations of ChatGPT, as well as ensuring the system does not produce dangerous medical content (Wang et al., 2023).

Costs

Costs of implementing and maintaining new technologies within healthcare institutions may represent a barrier to adoption. To manage data across different departments and share it with other health institutions, hospitals have to invest in costly software and equipment. However, some organizations work separately which makes the tracking and caring for patients difficult, as they sometimes need to be in different locations and receive different medical services

(Panch et al., 2019). AI models must remain simple in their characteristics and functions (Mennella et al., 2024).

Development costs are also significant. “Watson for Oncology”, is the AI system developed by IBM, set to recommend the most accurate cancer treatment. However, this system had proved to have little success and a very low return on investment, with the MD Anderson hospital abandoning the project after spending $60 million dollars (Ross & Swetlitz, 2017). Finally, costs of regulatory compliance may favor well-resourced institutions (Panch et al., 2019).

AI skills gap

The AI skills gap and the lack of expertise at the management and technical levels remain as obstacles (Moldoveanu, 2019), especially during the early development phase of the technology (Singh et al., 2020). This poses an issue when it comes to teaching non-experts how to use and interpret results recommended by AI tools, as well as how to react quickly in the event of problems. Additionally, the lack of AI experts and physicians during the training phase may affect data quality (Albahri et al., 2023). One reason for the shortage of skilled professionals is the attractiveness of other sectors using AI that are more fast-moving, such as electromobility, in comparison to the healthcare which is highly regulated and has been developing at a slower pace (Apell & Eriksson, 2023).

Given the importance of considering the barriers to adoption and challenges that AI digital tools can pose in healthcare, it is essential to explore the frameworks that help us assess drivers and impediments of successful implementation of these technologies. In the following section, we explore several management theories that help explain adoption and acceptance of AI technologies by healthcare professionals and patients.

2.4. Theoretical Framework

To structure the development of hypotheses in this study, several established management and technology adoption theories were used.

2.4.1 Technology Acceptance Model and Diffusion of Innovation

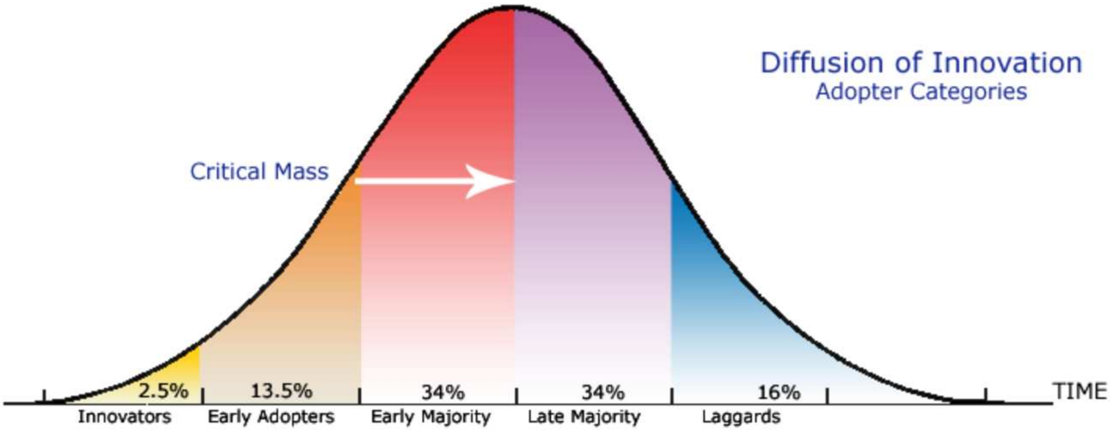
To predict if French patients will accept the use of AI in medical consultations, it is paramount to understand the factors that contribute to their acceptance.

The Technology Acceptance Model (TAM) was originally introduced by Davis (1985), and explains that perceived usefulness and perceived ease of use are key drivers of technology acceptance. Perceived usefulness refers to the extent to which an individual believes the technology will improve their performance, while perceived ease of use is the belief in the effortless use of the technology (Davis, 1985). Since then, TAM has been widely applied in various studies to predict and explain users' behavioral intention to use an innovative technology (King & He, 2006).

The Unified Theory of Acceptance and Use of Technology (UTAUT) first introduced by Venkatesh et al. (2003), is used to assess the drivers of acceptance of an innovation. This model was based on TAM, but with the introduction of new constructs such as social influence and facilitating conditions. Social influence describes the extent to which an individual believes that significant others consider the use of the new system to be expected, and facilitating conditions refers to the degree of which individuals perceive an institution possesses the adequate infrastructure for the successful implementation and use of the technology (Venkatesh et al., 2003).

However, critics have questioned the applicability of TAM and UTAUT across various technological innovations, highlighting their limited ability to capture the complexity of technologies without additional frameworks like the Diffusion of Innovation (DOI) (Venkatesh et al., 2012). According to Rogers (1986), an innovation is an idea that is perceived as new by an individual while diffusion is the process by which the innovation is communicated through channels. As seen in Figure 5, Rogers distinguishes adopters by categories, suggesting that as innovators adopt the technology, it encourages broader acceptance, gradually leading to increased adoption by others. However, the ultimate goal of this theory is to satisfy the needs of all category of adopters (Kaminski, 2011).

Figure 5: Diffusion of Innovation of Adopter Categories over time



Source: (Canadian Journal of Nursing Informatics, 2011)

By incorporating the DOI framework with TAM (Davis, 1985) and UTAUT (Venkatesh et al., 2003), we can better explain the AI acceptance of French patients in primary care.

2.4.2 Trust in Human-AI Collaboration

To determine if French patients will rely on AI diagnosis, it is important to consider trust, an essential component of acceptance of AI in healthcare. In a high stakes environment such as healthcare where the consequences of error can be significant (Hoff & Bashir, 2015), trust is fundamental for healthcare professionals to rely on AI for decision making (Siau & Wang, 2018). Additionally, a lack of trust in AI presents an obstacle in the adoption and the continuous progress of this technology in healthcare (Asan et al., 2020).

Trust in AI systems is defined based on three components: benevolence, integrity and ability of the technology (Asan et al., 2020). The level of trust a person has determines that person's behavior and defines the way they interact with technologies (Siau & Wang, 2018). Nevertheless, trust is complex and hard to measure as it is relational and specific to one's beliefs, culture and context (Gille et al., 2020).

Literature documented some crucial factors contributing to the enhancement of trust in AI technologies in healthcare. Transparency, which is the explainability of capabilities and limitations of the system, robustness which refers to the ability of the model to maintain reliable performance over time, and finally fairness which means the absence of unfair biases by the model, are components contributing to the enhancement of trust in AI systems (Asan et al., 2020).

2.4.3. Risk Based Theories

Perceived risks are defined by Mitchell (1999) as consumer's subjective expectation of loss. According to the author, the consumer assess risk through two components - the perceived severity of negative consequences and the perceived probability that these consequences will happen. Perceived risks are subjective and depend on the consumer's personal judgment, reflecting how risky they feel a situation is, rather than the actual level of risk involved (Mitchell, 1999).

A study conducted in France aimed at assessing patients' views of wearable devices (Tran et al., 2019). Results showed that patients main concerns related to perceived risks were driven by three factors. 28% of the patients were concerned that AI will replace human intelligence and caregivers. Additionally, 14% feared a misuse of private data, and 13% reported a serious risk for hacking. Therefore, the primary perceived risk of AI is patients' desire to maintain the human element in their healthcare experience (Tran et al., 2019).

Harm is another factor enhancing the perceived risk of an AI technology in healthcare. Studies have shown that patients are concerned about AI potentially harming their health. To address the perceived risk of harm, patients expect clinicians to take responsibility for ensuring the safety of AI tools. They also emphasize the importance of stronger regulatory safeguards and believe that doctors should consistently oversee and reevaluate AI-generated recommendations (Richardson et al., 2021).

Based on the mentioned theoretical framework, the conceptual model (Appendix B) divides trust in AI in three main components: perceived usefulness, demographics and AI familiarity, and perceived risks. Demographics and AI familiarity influence perceived usefulness and perceived risks. In return, these three components influence the behavioral intention of patients to accept AI in primary care, which shapes their preference of trusting an AI diagnosis over a doctor's one.

3. Methodology

This section explains the steps employed during the design of the research, describes data collection strategies, the sample size, and the procedures of the quantitative analysis.

3.1. Research Design

The objective of the conducted study is to assess French patient's perception of the use of AI in primary care consultations. The following Figure 6 summarizes the steps and methodology implemented throughout the research.

Figure 6: Research Design

Introduction	Determination of research scope
	Validation of research question
	Formulation of research question
Literature Review	Identification of pertinent theory and empirical studies
	Analysis of empirical study via literature review
Methodology	Development of research question via stepwise approach
	Development of survey via Qualtrics
	Collection of quantitative data via forums and social media
Analysis and Discussion	Quantitative analysis via Python
Conclusion	Interpretation of managerial implications
	Explanation of limitations and future considerations

3.2. Data collection

To assess French patients' perception of the use of AI in primary care, a quantitative survey was designed on Qualtrics to undercover behavioral dimensions (Lim, 2024). This survey was inspired by and formatted according to the empirical study called "Assessing Yemeni university students' public perceptions toward the use of artificial intelligence in healthcare" (Hatem et al., 2024). Accordingly, some questions were adopted directly, while others were adapted to suit the specific context of this study.

At the beginning of the survey, participants were greeted by a message explaining the goal of the research, the length of it in minutes as well as an information indicating their responses are anonymous. Additionally, primary care was defined for better understanding of the healthcare scope.

The survey consisted of 35 questions divided into four principal blocks, namely Demographics and AI Familiarity (N=9), Relationship Patient/Doctor (N=7), Benefits and Positivity toward AI in Healthcare (N=7), Concerns and Fears (N=10), and Trust and Confidence in AI (N=3). The survey questions consisted of multiple-choice answers and 5-point Likert-Scale format. The first question of the survey targets French citizens or individuals living in France. An attention question was also incorporated to exclude participants answering randomly. The survey was distributed on social media and relevant forums, and employed non-probability method, namely convenience and snow-ball sampling. As the survey comprises 35 questions, the aim was to receive 315 responses. The survey questions are outlined in the Appendix A. Appendix B shows the domains and items used by (Hatem et al., 2024) compared to the ones used in this thesis. Blank cells represent the differences between the two surveys.

A total of 277 individuals initiated the survey. After filtering the data for participants who completed the questionnaire, are French citizens or residing in France, and succeeded to the attention question, **188** participants were retained.

3.3. Variable Measurement

The dependent variable chosen to assess French patients' perception of the use of AI in primary care consultations refers to the question 35 of the survey "I would trust the assessment of an artificial intelligence more than the assessment of a doctor".

The first method adopted consisted of uncovering underlying dimensions. We have isolated the question 9 of the survey "For which purposes do you primarily use AI tools?" by retaining participants who may or may have not picked the answer "Whenever I feel sick". This approach allowed us to create two distinct groups, people who use AI tools for self-health diagnosis, and people who do not. 107 participants use AI tools whenever they feel sick and 81 do not.

The second step involved dimensionality reduction and the identification of underlying patterns among related variables. After executing a scree plot, we have retained two factors: "Acceptance" which combines survey items related to AI acceptance, and "Fear_Risk" which consists of items reflecting concerns or reluctance toward the use of AI.

Finally, to test the 8 hypotheses, an ordinal regression was conducted. Ordinal regressions are used to uncover underlying dimensions of surveys employing Likert-scale (Tutz, 2021). The factors mentioned previously were used as control variables. Other items were also controlled for, as revealed in the next section. Figure 7 describes the null hypotheses developed, the independent variables used in the regression, and their related pertinence with management theories.

Figure 7: Hypotheses development and management theories related pertinence

Hypotheses	Independent Variables	Management Theories
H1: There is no relationship between AI familiarity and AI acceptance.	Q7: How frequently do you interact with AI technologies in your daily routine?	TAM/UTAUT
H2: There is no relationship between seeking second opinions and AI acceptance.	Q16: Have you ever sought a second opinion on your diagnosis? - Drag to your answer	Risk-Based Theories
H3: Perceived AI fairness does not increase trust.	Q19: Artificial intelligence in primary care, will reduce discrimination. - Drag to your answer	Trust in Human-AI Collaboration

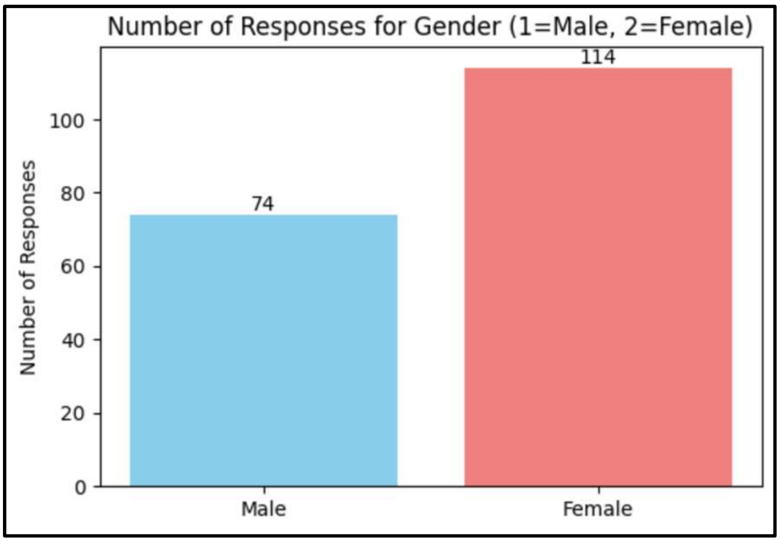
Hypotheses	Independent Variables	Management Theories
H4: Belief in AI's patient benefits does not influence support.	Q17: I think that the use of artificial intelligence brings benefits for the patient. - Drag to your answer	TAM/UTAUT
H5: There is no difference between women and men in their acceptance of an AI-based diagnosis over a doctor's diagnosis.	Q2: "How do you identify?"	UTAUT (Social Influence)
H6: There is no relationship between patients' acceptance of AI in healthcare and their preference for AI-based diagnoses over doctor diagnoses.	Factor: "Acceptance"	TAM + Trust Theory
H7: There is no relationship between patients' fear of AI in healthcare and their preference for a doctor having final authority over AI recommendations. Here DV= Q33	Factor: "Fear_Risk"	Risk-Based Theories
H8: The relationship between fear of AI and trust in AI does not differ based on patients' level of AI acceptance.	Interaction terms: "Acceptance" * "Fear_Risk"	Trust + Risk-Based Theories

4. Results

This final section shows the results of the quantitative survey. The first sub-section describes the participants overview, their demographics and AI familiarity. The second sub-section highlights the underlying patterns through the isolation of the Q9 variable and the factor-analysis. Finally, the last sub-section shows the testing of the hypotheses.

4.1. Participants overview

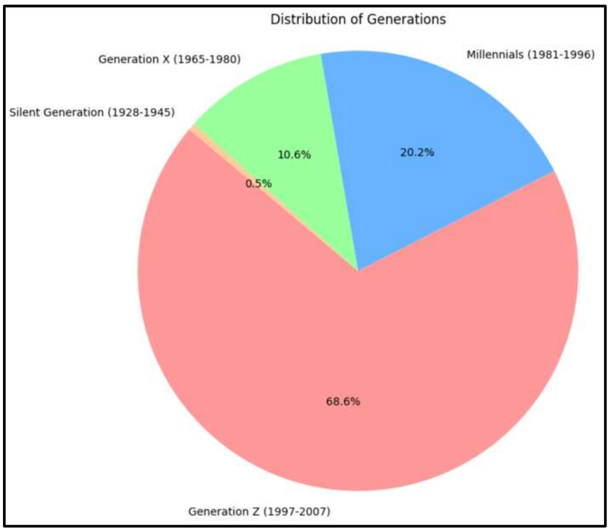
Figure 8: Gender distribution of participants



Note. Survey responses from n = 188 participants.

Figure 8 represents the gender distribution of participants. Most respondents were females with n = 114. Only 74 men participated in the survey.

Figure 9: Distribution of generations



Note. Survey responses from n = 188 participants.

Figure 9 highlights that the largest generation of respondents was the Generation Z which accounted for 68.6% of the entire dataset, followed by Millennials (20.2%), Generation X (10.6%) and finally Silent Generation (0.5%). This showcases a large distribution of young participants.

The largest group held a master's degree (53.2%) followed by those with a bachelor's degree (31.9%). 8.5% held a high-school degree, 2.7% a Phd, and only 5.3% held a brevet diploma. This revealed that most respondents had a higher level of education.

On one hand, most respondents (19.1%) had an income below 20.000€ or did not have any source of income at all (19.7%). 18.6% fell within the 35.000€-50.000€ and above 50.000€. Alternatively,, 42% of participants were employed full-time followed by 40.4% of students. 9.6% of them were self-employed and only a small proportion <5% were either part-time employed, unemployed, or retired. This indicated that a large proportion of participants were students or full-time employed, with an income below 20.000€, or had no source of income at all.

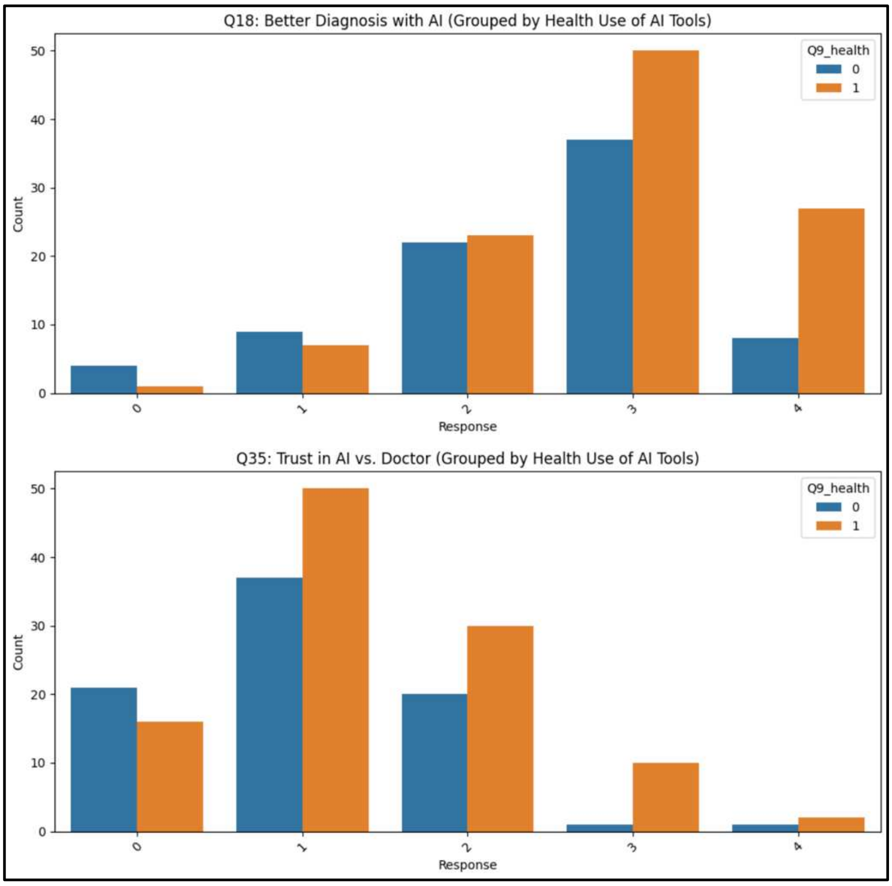
Regarding AI familiarity, almost half of the respondents reported using AI tools "very often" (45.2%), followed by 29.3% "often", 14.5% "sometimes", 6.9% "rarely" and only 3.1% stated never using AI tools.

4.2. Preliminary analysis and identification of underlying dimensions

To identify underlying patterns, we decided to first isolate “Q9: For which purposes do you primarily use AI tools?”.

Figure 10 shows the designed two groups of participants: those who use AI for self-health diagnosis (group 1) and those who don’t (group 0). We used “Q18: Through the use of artificial intelligence, there will be better diagnosis in the future” and “Q35: I would trust the assessment of an artificial intelligence more than the assessment of a doctor” as dependent variables. The bar plot highlights a significant difference between the two groups as 27 participants of group 1 would strongly agree that through AI there will be better diagnosis in the future, compared to 8 participants belonging to group 0. Furthermore, the number of participants in group 0 who disagreed more than those in group 1 for the same item is higher. Finally, 10 participants of group 1 agreed that they would trust AI diagnosis more than a doctor’s diagnosis, compared to only one participant belonging to group 0. Moreover, 21 respondents of group 0 strongly disagreed with Q35 compared to 16 respondents of group 1. This further demonstrated the difference in perception based on the use of AI tools for self-health diagnosis.

Figure 10: Differences in how patients perceived Q18 and Q35 based on their use of AI tools for self-health diagnosis



In order to uncover underlying behavioral aspects, we conducted an exploratory factor analysis on a set of theoretically motivated items. Factors that loaded strongly (≥ 0.4) or improved the internal consistency (Cronbach's Alpha) were retained. This process resulted in two reliable factors "Fear_Risk" and "Acceptance" as composed of the following items below. A screeplot was also performed to confirm the number of factors: two (see Appendix C).

Fear_Risk:

"Q25: Artificial intelligence should not be used in medicine as a matter of principle."

"Q27: The influence of Artificial Intelligence on medical treatment scares me."

"Q30: I am worried that Artificial Intelligence-based systems could be manipulated from the outside (terrorists, hackers, …)."

"Q29: I am more afraid of a technical malfunction of Artificial Intelligence than of a wrong decision by a doctor."

Acceptance:

"Q15: Do you trust the diagnosis made by a doctor?"

"Q13: Have you ever had the impression that a doctor lacked understanding of your personal needs or concerns?"

"Q21: By using Artificial Intelligence, doctors will have more time for the patient."

"Q23: The use of artificial intelligence will reduce the workload of doctors."

"Q20: Artificial intelligence in primary care will benefit to those with less accessibility"

"Q11: Have you ever been misdiagnosed by a doctor?

"Q22: The use of artificial intelligence is an effective instrument against the overload of doctors and the shortage of doctors."

"Q18: Through the use of artificial intelligence, there will be better diagnosis in the future.

"Q24: Doctors will play a less important role in the primary care of patients in the future"

Figure 11 represents the factors loadings. Factor 1 is related to "Fear_Risk" and factor 2 to AI "Acceptance".

The core items with the highest absolute values for factor 1 were mostly related to fear or objection of AI (Q25, Q27, Q29, Q30). This revealed that participants who scored higher on these items tended to agree more with statements expressing fear, worry, concerns and objection to AI in medicine. The negative moderate load of Q18 (-0.586) indicated that individuals agreed less with the statement that AI will lead to better diagnosis.

Regarding factor 2, the variables scoring the highest absolute values were Q22 and Q23, and moderate values Q18, Q20 and Q21. These values loaded positively, suggesting that individuals who scored high on factor 2 tended to agree more with statements about AI improving workload, accessibility and diagnosis, and potentially changing the doctor's role.

Figure 11: Factor Loadings of "Fear_Risk"and "Acceptance"

Factor Loadings:

	Factor 1	Factor 2
Q25: Artificial intelligence should not be used...	0.791	-0.076
Q27: The influence of Artificial Intelligence o...	0.820	0.030
Q30: I am worried that Artificial Intelligence-...	0.387	0.019
Q29: I am more afraid of a technical malfunctio...	0.661	-0.087
Q15: Do you trust the diagnosis made by a doctor?	-0.106	0.092
Q13: Have you ever had the impression that a do...	-0.046	-0.223
Q21: By using Artificial Intelligence, doctors ...	-0.230	0.590
Q23: The use of artificial intelligence will re...	-0.236	0.698
Q20: Artificial intelligence in primary care wi...	-0.208	0.569
Q11: Have you ever been misdiagnosed by a doctor?	-0.006	-0.205
Q22: The use of artificial intelligence is an e...	-0.367	0.732
Q18: Through the use of artificial intelligence...	-0.586	0.423
Q24: Doctors will play a less important role in...	0.118	0.296

In order to ensure that the variables selected had internal consistency, a Cronbach Alpha of the two factors was conducted. The α value for the "Acceptance" factor scored at 0.766, while the α value for the "Fear_Risk" factor reached 0.759. These two alpha scores being higher than 0.7, indicated a high reliability to capture the intended underlying constructs (Tavakol & Dennick, 2011) of Acceptance and Fear of AI in primary care consultations.

The next step consisted of conducting a Multivariate Analysis of Variance (MANOVA) to evaluate if groups differ on a set of related outcomes (French, et al., 2008). This was used to examine whether French patients' use of AI for health purposes was associated with their attitudes toward AI in primary care consultations (see Appendix D). We used the combined effect of group 0 and group 1 on the two factors as dependent variables. The analysis revealed a robust statistical significance of the multivariate effect of AI use on attitudes, with Wilk's Lamba equaling 0.9036, F-value reaching 9.867 and a p-value of 0.0001. Additionally, a t-test was performed to further confirm the difference between the two group means. The two p-values of 0.016 and 0.020 validated the statistical difference between group 0 and group 1 in their perceived benefits and fear toward AI use in primary care consultations. The MANOVA analysis and the t-test provided additional evidence of our previous findings that patients who used AI for self-health diagnosis differed significantly in their acceptance and level of concerns toward AI diagnosis, compared to those who do not use it in this context.

We then conducted an ordinal regression analysis with two subsets of groups: group 0 and group 1. However, the observation suggested that the effect of the independent variables (refer to

Figure 7) on the dependent variable (Q35), was not drastically different between the two groups. In fact, when analyzing the two groups separately, the sample size was reduced to N=109 group 1 and N=79 for group 0. This reduced the sample data drastically, which reduced the statistical power to detect significant relationships. For this matter, we decided to combine the two groups and use the initial dataset of N=188, leading to greater power and an easier detection of significance.
The ordinal regression findings are displayed and commented on in the next sub-section.

4.3 Hypotheses Testing

Starting with the predictors, we ran multivariate regression analysis using "Acceptance" and "Fear_Risk" as predictors to predict Q35. At first, gender (Q2), age (Q3), employment status (Q4) and level of education (Q5) were added alongside the factors. All variables were significant (
Figure *12*) except for age and level of education. Thus, Q2 and Q4 as well as the two factors were retained as predictors for regressions of H1 through H5 (
Figure *12*).

Figure 12: Ordinal Regression of first predictors

	coef	std err	z	P>|z|
Acceptance	0.1913	0.093	2.056	0.040
Fear_Risk	0.3890	0.096	4.052	0.000
Q2: How do you identify?	-0.4117	0.166	-2.485	0.013
Q3: In what year were you born?	0.0832	0.125	0.665	0.506
Q4: Please indicate your employment status	-0.2097	0.078	-2.671	0.008
Q5: What is your highest degree or level of education?	-0.0675	0.075	-0.904	0.366

To test H1, we examined the effect of gender (Q2) on Q35, keeping all other variables ("Acceptance and "Fear_Risk") constant. With coef = -0.242 and a p-value equaling 0.142, we failed to reject the null hypothesis that there was no difference between men and women in their acceptance of AI diagnosis over a doctor's diagnosis.

To test H2, we used Q7 "How frequently do you interact with AI technologies in your daily routine?", the two factors, Q2 and Q4 as predictors. With a positive coefficient of 0.142 and a p-value of 0.075, we failed to reject the null hypothesis that there was no relationship between AI familiarity and AI acceptance. This model also revealed that gender (Q2), was initially not significant when only the two factors were included in the model. After adding Q4 and Q7 as predictors, the statistical significance of gender increased (p-value=0.004). This suggested that the effect of gender was suppressed whereby its influence on trust in AI diagnosis was previously masked by shared variance with other variables. Gender's unique predictive role was better explained when differences in employment status and familiarity with AI are also considered.

The H3 hypothesis was tested to observe whether there was a difference in the trust placed in AI diagnoses by patients who sought a second opinion on their doctor's diagnosis. For this purpose, Q16 was placed as a predictor alongside Q2, Q4 and the two factors. The lack of statistical significance associated with the p-value (= 0.405), indicated that we did not have sufficient evidence to reject the null hypothesis.

The fourth hypothesis examined whether patients perceive AI in primary care as a way to reduce discrimination. Thus, Q19 was chosen as a predictor. Keeping all other variables constant (Q2, Q5, factor "Acceptance" and "Fear_Risk"), Q19 was associated with a statistically significant increase (0.1937) in the log-odds of being in a higher category of trust in AI's diagnosis. This finding suggested that patients who agreed AI reduced discrimination tended to have a greater trust in AI's diagnosis capability.

To test H5, the purpose was to identify if participants perceived AI as an innovation that will bring benefits for the patients. Thus, Q17 was retained as a predictor. Keeping Q2, Q4 and the two other factors constant, the odds of being in a higher category of trust in AI's diagnosis were statistically significantly (p-value = 0.026) higher by 0.2828, for individuals in the group represented by a one-unit increase in Q17.

Regarding H6, we chose to only keep the Acceptance factor as the predictor variable. The ordinal regression model found that the Acceptance factor significantly predicted patients' trust in AI's diagnosis. The effect was statistically significant with a positive coefficient of 0.392 and a p-value <0.001. This indicated that general openness of participants to AI was positively associated with willingness to trust AI generated diagnoses over those made by a physician.

For H7, an ordinal regression was performed to test whether fear of AI (Fear_Risk factor as a causal variable) predicted respondents' agreement with the statement "A doctor should always have the final word over a diagnosis" (Q33). The aim was to assess perceived competence of doctors in working with AI technologies. The model found a negative direction of the coefficient, revealing that individuals with high fear scores were less likely to support exclusive decision-making made by a doctor. Nevertheless, the result did not provide enough statistical evidence ($\beta = -0.0118$, p-value = 0.220) to confirm a relationship between Fear_Risk factor and Q33.

Finally, H8 was tested by incorporating as predictors both factors and their interaction term. The aim was to test whether fear might change the effect of acceptance. In this model, both Acceptance ($\beta = 0.361$, $p < .001$) and Fear_Risk ($\beta = 0.341$, $p < .001$) were found to be statistically significant predictors. This indicated that patients who expressed openness toward the integration of AI in healthcare, as well as those who reported more fear or concern, were more likely to trust AI's diagnosis in primary care. Interestingly, the interaction term was negative and approached significance ($\beta = –0.180$, $p = .079$). This finding revealed that when patients were both highly accepting and highly fearful of AI, the positive effect of acceptance on trust became weaker. In other words, fearing AI might reduce patients' acceptance on AI's diagnosis. Nonetheless, the result was not statistically significant enough to allow for a definitive interpretation.

5. Discussions

This study aimed at evaluating the perception of French citizens' or individuals residing in France concerning AI in primary care. The results of this study amplify existing research on patient perspectives regarding AI in healthcare. This section summarizes the findings and gives theoretical implications.

Our analysis identified two key psychological factors that influenced patient attitudes: "Acceptance", and "Fear_Risk".

On the one hand, we found that patients who score high in Acceptance demonstrated significantly greater trust in AI-generated diagnoses (Q35). Patients who viewed AI as being beneficial for instance by improving diagnosis accuracy, reducing doctor's workload or enhancing accessibility (Acceptance factor), were more open to its use. This finding further supports the Technology Acceptance Model theory that perceived usefulness drives technology adoption (Davis, 1985).

Additionally, the UTAUT model highlighting social influence and facilitating conditions (Venkatesh et al., 2003) was partially supported. Indeed, the relationship between AI familiarity (Q7) and trust (Q35), were not statistically significant, indicating that exposure to AI does not necessarily translate in enhanced trust in AI medical diagnosis. This suggested that AI use should be evaluated differently by differentiating general AI use from healthcare specific application. In fact, the results emerging from our analysis of Q9_health revealed that patients already using AI for self-healthcare diagnosis expressed greater acceptance and less fear toward AI technologies compared to the opposite group. This finding further justifies the fact that while Venkatesh et al. (2003) suggest that general AI familiarity drives adoption, our results indicate that domain-specific experience might be more predictive of AI acceptance than overall tech-savviness (Q7).

On the other hand, individuals who expressed "Fear_Risk" toward AI diagnosis were less likely to accept it (Q35). This factor specifically capturing concerns over technical malfunction (Q29), external manipulation (Q30) or deterioration of the doctor-patient relationship (Q31), reflected ethical considerations raised in prior research (Karimian et al., 2022; Murdoch, 2021).

Interestingly, while the Fear factor did not show statistical significance when predicting preference for physician authority (H7), the interaction term between “Acceptance” and “Fear_Risk” (H8) suggested that when patients both accept AI but afraid of it at the same time, the positive effect of acceptance can be dampened by fear. While this moderation effect doesn't reach conventional significance thresholds, it underscores ethical and security considerations which must be taken into consideration to increase trust, as highlighted in the literature such as bias in AI algorithms (Norori et al., 2021), accountability gaps (Naik et al., 2022) and regulatory frameworks (EU Artificial Inteligence Act, 2024).

We also observed a suppression effect with the gender item. Although initially not statistically significant, gender became a more meaningful predictor when we controlled for employment status and AI familiarity. This suggested that demographic influence on trust may impact trust in AI when considered alongside user’s experience and technological exposure. This outcome extends on the UTAUT’s framework on social conditions (Venkatesh et al., 2003).

Notably, patients who believed AI could reduce discrimination (Q19), showed a statistically significant higher trust in AI acceptance. This showcased a social benefit perceived by patients, revealing that AI could act more objectively and with less social biases than human doctors. It also underscored the important of developing transparent AI systems.

6. Limitations and Future Research

While providing theoretical valuable insights, it is important to acknowledge the limitations of this study.

First, the literature review was limited to documents focusing on healthcare specialties, such as gynecology and cardiology. There were limited recent studies focusing on primary care available. Regarding the analysis section, this study was composed of 276 answers with only 188 complete ones. Recognizing the importance of sample size, smaller responses may have led to little statistical significance of some items. Additionally, the geographical disparity included in the literature part was not reflected in the survey. Indeed, this study primarly focused on the perceptions of French citizens or individuals residing in France, wich means no question was assessed on the location. This contributed to a higher response rate. According to the geographical data provided by Qualtrics, most responses came from Europe particularly from Germany and France, as well as from North Africa. As a result, the survey did not provide meaningful insights on the geographical differences in perception of AI in pimary care consultations. Finally, due to space and time constraints, the lack of expert's interviews did not bring in-depth qualitative data, allowing the research to focus on doctor's opinions of the use of AI in primary care consultations.

Taking into consideration these limitations, as well as the rapid development of AI technologies, future research should aim for higher response rate with geographical data and include expert's interviews to better understand societal, ethical and psychological implications of AI in primary care consultations.

7. Conclusion

This study shed light on how French patients perceive the use of AI technologies in primary care consultations. It reviewed the current literature research on digital transformation, dissatisfaction with medical consultations in France, as well as the use of AI in healthcare in France. Particularly, it highlighted the potential healthcare benefits offered by AI such as increased efficiency, better accessibility and diagnostic accuracy. The quantitative analysis was established through the lenses of management theories such as the TAM, UTAUT and risk-based theories, providing an essential framework to structure the development of hypotheses.

The quantitative results revealed that while acceptance is driven by perceived benefits, fear persists around ethical considerations and reliability of AI systems. In a high-risk environment like healthcare, addressing these concerns is paramount for the successful implementation of AI in primary care consultations. By ensuring unbiased AI diagnoses, clear communication about entities' responsibilities and robust safeguards, French patients' perception could shift toward greater trust and less fear of AI technologies in future primary care consultations.

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9. Appendices

9.1 Appendix A: Survey Design

AI in Primary Care Consultations: How French Patients Perceive Health Analyses by LLMs

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Start of Block: Block 4

Q0 Welcome to the Survey! Thank you for taking the time to participate. This survey is part of a research study exploring how individuals in France perceive the use of artificial intelligence (AI) in primary care. Primary care refers to the initial point of contact between a patient and a general practitioner, focusing on assessing the patient's condition and establishing a diagnosis. Your responses are anonymous and will only be used for research purposes. The survey will take approximately 5–10 minutes. P.S: This survey contains Karma to get free survey responses at SurveySwap.io Click "Next" to begin.

End of Block: Block 4

Start of Block: Demographics and AI use

Q1 Are you a french citizen or residing in France?

- ○ Yes (1)
- ○ No (2)

Skip To: End of Survey If Are you a french citizen or residing in France? = No

Q2 How do you identify?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)

Q3 In what year were you born?

- 1928-1945 (1)
- 1945-1964 (2)
- 1965-1980 (3)
- 1981-1996 (4)
- 1997-2007 (5)

Q4 Please indicate your employment status

- Self Employed (1)
- Part-time employed (2)
- Full-time employed (3)
- Student (4)
- Retired (5)
- Unemployed (6)
- Other (7)

Q5 What is your highest degree or level of education?

◯ Brevet Diploma (1)

◯ High School Degree (2)

◯ Classes Préparatoires (3)

◯ Bachelor's degree (4)

◯ Master's degree (5)

◯ PhD (6)

◯ No Degree (7)

◯ Other (8)

Q6 Please state your approximate annual personal gross income (before tax and social contributions) in €.

◯ Below €20,000 (1)

◯ €20,000 – €35,000 (2)

◯ €35,000 – €50,000 (3)

◯ Above €50,000 (4)

◯ I do not have any income (5)

◯ Prefer not to say (6)

Q7 How frequently do you interact with AI technologies in your daily routine?

- ○ Never (1)
- ○ Rarely (2)
- ○ Sometimes (3)
- ○ Often (4)
- ○ Very often (5)
- ○ I don't know / Not sure (6)

Q8 Which AI tool(s) do you use?

- ▢ ChatGPT (1)
- ▢ Google Gemini (2)
- ▢ Claude (3)
- ▢ DeepSeek (7)
- ▢ Jasper AI (4)
- ▢ Other (5) ____
- ▢ I do not use AI tools (8)

Q9 For which purposes do you primarily use AI tools?

- ▢ Personal purpose (recipes, gaming ideas...) (1)
- ▢ For my studies (exams, thesis...) (2)
- ▢ For work (content generation, business plan, calculations...) (3)
- ▢ Whenever I feel sick (soar throat, fever, skin problems...) (7)
- ▢ For general knowledge (history, business, finance...) (4)
- ▢ I do not use AI tools (5)

End of Block: Demographics and AI use

Start of Block: Relationship Patient/Doctor

Q10 How often do you go to the doctor?

	0= Very rarely	1= Sometimes	2= Often	3= Most of the time	4= Every time I feel sick
	0	1	2	3	4
Drag to your answer ()					

Q11 Have you ever been misdiagnosed by a doctor?

- ○ Yes (1)
- ○ No (2)

Q12 Have you ever felt that a doctor did not spend enough time to properly diagnose you?

- Yes (1)
- No (2)

Q13 Have you ever had the impression that a doctor lacked understanding of your personal needs or concerns?

- Yes (1)
- No (2)

Q14 Have you ever felt uncomfortable when the doctor was typing on their computer or writing?

- Yes (1)
- No (2)

Q15 Do you trust the diagnosis made by a doctor?

- Yes (1)
- No (2)

Q16 Have you ever sought a second opinion on your diagnosis?

	0= Never	1= I thought of it, but did not at the end	2= Once	3= More than once	4= Almost every time
	0	1	2	3	4
Drag to your answer ()					

End of Block: Relationship Patient/Doctor

Start of Block: Benefits and Positivity Toward AI in Healthcare

Q17 I think that the use of artificial intelligence brings benefits for the patient.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q18 Through the use of artificial intelligence, there will be better diagnosis in the future.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q19 Artificial intelligence in primary care, will reduce discrimination.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q20 Artificial intelligence in primary care will benefit to those with less accessibility

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4

Drag to your answer ()	

Q21 By using Artificial Intelligence, doctors will have more time for the patient.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q22 The use of artificial intelligence is an effective instrument against the overload of doctors and the shortage of doctors.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q23 The use of artificial intelligence will reduce the workload of doctors.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

End of Block: Benefits and Positivity Toward AI in Healthcare

Start of Block: Concerns and Fears

Q24 Doctors will play a less important role in the primary care of patients in the future.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q25 Artificial intelligence should not be used in medicine as a matter of principle.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q26 Doctors are becoming too dependent on computer systems.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q27 The influence of Artificial Intelligence on medical treatment scares me.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q28 The use of Artificial Intelligence prevents doctors from learning to make their own correct judgement of the patient.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q29 I am more afraid of a technical malfunction of Artificial Intelligence than of a wrong decision by a doctor.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q30 I am worried that Artificial Intelligence-based systems could be manipulated from the outside (terrorists, hackers, …).

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q31 The use of artificial intelligence weakens the doctor-patient relationship.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4

Drag to your answer ()	

Q32 Attention question: please put "Neutral" for this one

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q33 A doctor should always have a final word over the diagnosis.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

End of Block: Concerns and Fears

Start of Block: Trust and Confidence in AI and Doctors

Q34 If a patient has been harmed, a doctor should be held responsible for not following the recommendations of AI.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q35 I would trust the assessment of an artificial intelligence more than the assessment of a doctor.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

Q36 I would like my doctor to override the recommendations of Artificial Intelligence if they come to a different conclusion based on their experience or knowledge.

	0= Strongly Disagree	1= Disagree	2= Neutral	3= Agree	4= Strongly Agree
	0	1	2	3	4
Drag to your answer ()					

End of Block: Trust and Confidence in AI and Doctors

9.2 Appendix B: Differences in domains and items of both surveys

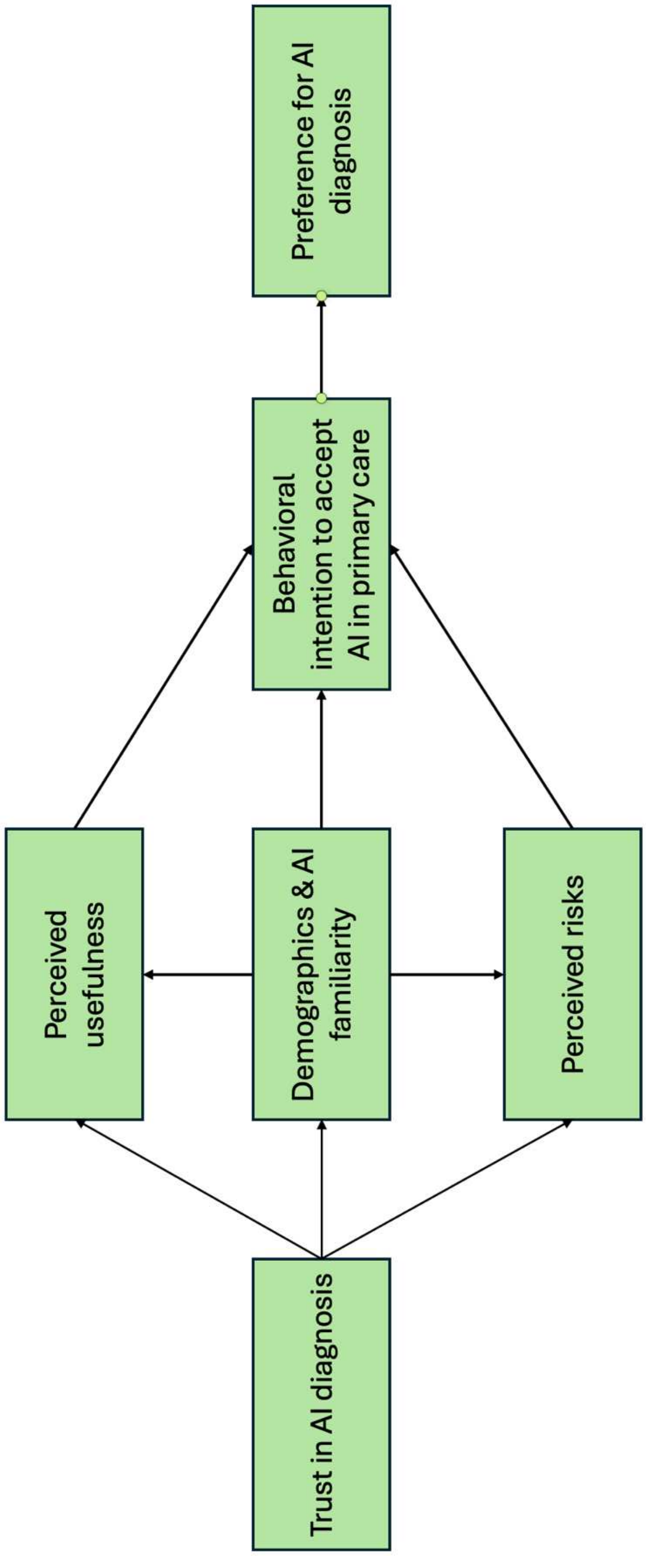
Domain / items	
(Hatem et al., 2024)	(Ben Abdallah, 2025)
	Demographics and AI Use
	Are you a French citizen or residing in France?
	How do you identify?
	In what year were you born?
	Please indicate your employment status
	What is your highest degree or level of education?
	Please state your approximate annual personal gross income (before tax and social contributions) in €
	How frequently do you interact with AI technologies in your daily routine?
	Which AI tool(s) do you use?
	For which purposes do you primarily use AI tools?
	Relationship Patient/Doctor
	How often do you go to the doctor?
	Have you ever been misdiagnosed by a doctor?
	Have you ever felt that a doctor did not spend enough time to properly diagnose you?
	Have you ever had the impression that a doctor lacked understanding of your personal needs or concerns?

	Have you ever felt uncomfortable when the doctor was typing on their computer or writing?
	Do you trust the diagnosis made by a doctor?
	Have you ever sought a second opinion on your diagnosis?
Benefits and Positivity Toward AI in Healthcare	
I think that the use of artificial intelligence brings benefits for the patient	I think that the use of artificial intelligence brings benefits for the patient
Through the use of artificial intelligence, there will be fewer treatment errors in the future	Through the use of artificial intelligence, there will be better diagnosis in the future
By using Artificial Intelligence, doctors will again have more time for the patient	By using Artificial Intelligence, doctors will again have more time for the patient
The use of artificial intelligence is an effective instrument against the overload of doctors and the shortage of doctors	The use of artificial intelligence is an effective instrument against the overload of doctors and the shortage of doctors
The use of artificial intelligence will reduce the workload of doctors	The use of artificial intelligence will reduce the workload of doctors
	Artificial intelligence in primary care will benefit those with less accessibility
	Artificial intelligence in primary care will reduce discrimination
Concerns and Fears	
Doctors will play a less important role in the therapy of patients in the future	Doctors will play a less important role in the primary care of patients in the future
Artificial intelligence should not be used in medicine as a matter of principle	Artificial intelligence should not be used in medicine as a matter of principle
Doctors are becoming too dependent on computer systems	Doctors are becoming too dependent on computer systems
The influence of Artificial Intelligence on medical treatment scares me	The influence of Artificial Intelligence on medical treatment scares me

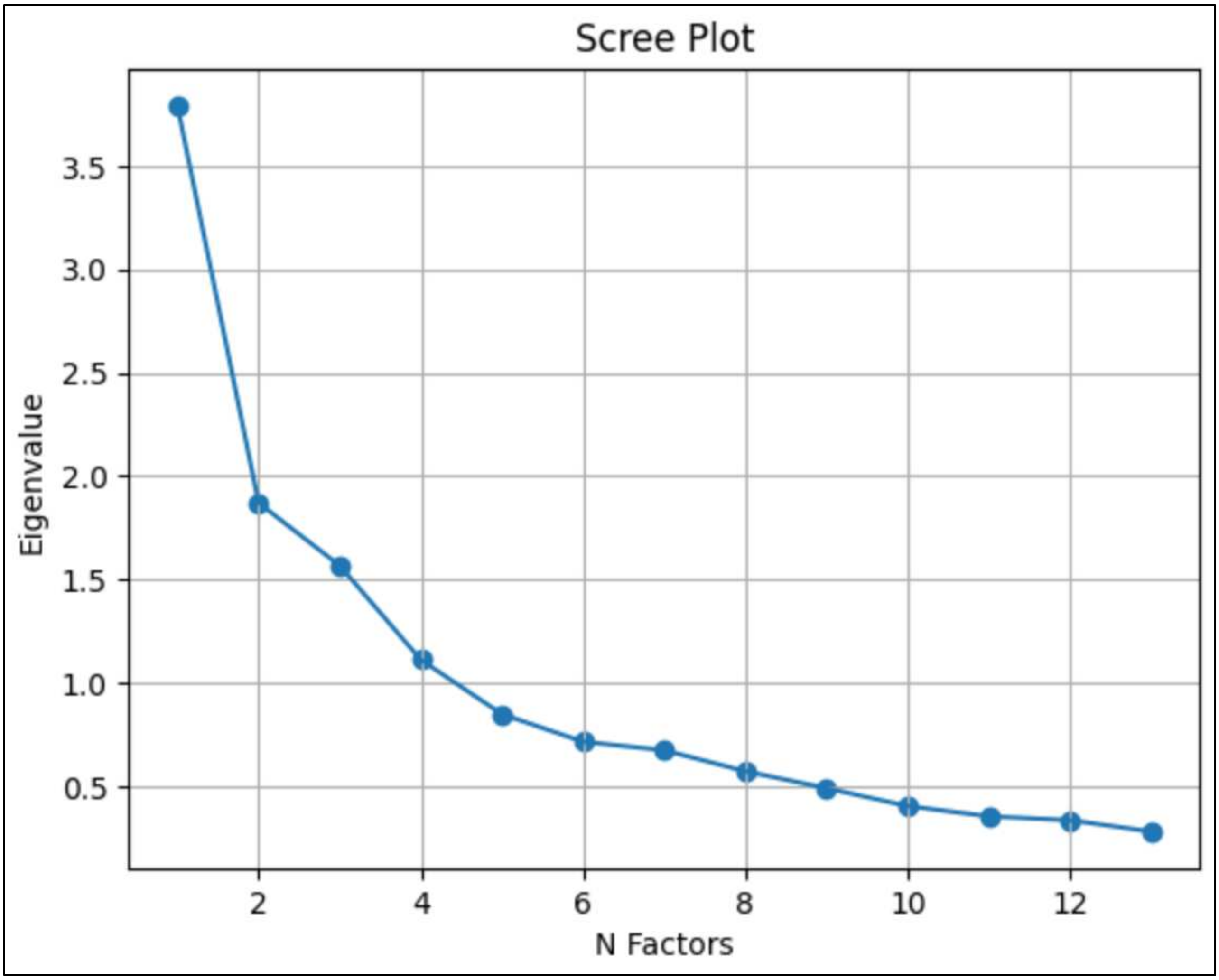
The use of Artificial Intelligence prevents doctors from learning to make their own correct judgement of the patient	The use of Artificial Intelligence prevents doctors from learning to make their own correct judgement of the patient
If AI predicts a low chance of survival for the patient, doctors will not fight for that patient's life as much as before	I am worried that Artificial Intelligence-based systems could be manipulated from the outside (terrorists, hackers, …)
I am more afraid of a technical malfunction of Artificial Intelligence than of a wrong decision by a doctor	I am more afraid of a technical malfunction of Artificial Intelligence than of a wrong decision by a doctor
I am worried that Artificial Intelligence-based systems could be manipulated from the outside (terrorists, hackers,…)	The use of artificial intelligence weakens the doctor-patient relationship
The use of artificial intelligence impairs the doctor-patient relationship	A doctor should always have a final word over the diagnosis
Trust and Confidence in AI and Doctors	
The testing of artificial intelligence before it is used on patients should be carried out by an independent body	
If a patient has been harmed, a doctor should be held responsible for not following the recommendations of AI	If a patient has been harmed, a doctor should be held responsible for not following the recommendations of AI
I would trust the assessment of an artificial intelligence more than the assessment of a doctor	I would trust the assessment of an artificial intelligence more than the assessment of a doctor
Doctors know too little about AI to use it on patients	
I would like my doctor to override the recommendations of Artificial Intelligence if he comes to a different conclusion based on his experience or knowledge	I would like my doctor to override the recommendations of Artificial Intelligence if he comes to a different conclusion based on his experience or knowledge
Patient Involvement and Data Sharing	
I would like my personal, medical treatment to be supported by Artificial Intelligence	

I would make my anonymous patient data available for non-commercial research (universities, hospitals, etc.) if this could improve future patient care	
Artificial intelligence-based decision support systems for doctors should only be used for patient care if their benefit has been scientifically proven	
I am not worried about the security of my data	
Professional Autonomy of Doctors	
The use of Artificial Intelligence is changing the demands of the medical profession	
A doctor should always have the final control over diagnosis and therapy	

9.3 Appendix C: Conceptual Framework



9.4 Appendix D: Scree Plot Output



9.5 Appendix E: MONOVA results

```
                  Multivariate linear model
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--------------------------------------------------------------
       Intercept        Value  Num DF  Den DF   F Value Pr > F
--------------------------------------------------------------
          Wilks' lambda 0.9423 2.0000 185.0000  5.6683 0.0041
         Pillai's trace 0.0577 2.0000 185.0000  5.6683 0.0041
 Hotelling-Lawley trace 0.0613 2.0000 185.0000  5.6683 0.0041
    Roy's greatest root 0.0613 2.0000 185.0000  5.6683 0.0041
--------------------------------------------------------------

--------------------------------------------------------------
       Q9_health        Value  Num DF  Den DF   F Value Pr > F
--------------------------------------------------------------
          Wilks' lambda 0.9036 2.0000 185.0000  9.8670 0.0001
         Pillai's trace 0.0964 2.0000 185.0000  9.8670 0.0001
 Hotelling-Lawley trace 0.1067 2.0000 185.0000  9.8670 0.0001
    Roy's greatest root 0.1067 2.0000 185.0000  9.8670 0.0001
==============================================================
```