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Review Article

Consumer Trust and Purchase Intention toward AI-Driven Personalized Healthcare and Digital Therapeutics

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ABSTRACT

Artificial Intelligence (AI) is transforming healthcare by enabling personalized support, digital therapeutics, and intelligent health management tools. From diabetes management applications to AI-powered medical chatbots, these technologies are increasingly influencing healthcare decisions. Despite rapid market growth, with the global AI healthcare market projected to exceed USD 110 billion by 2030, consumer adoption remains limited. A major factor underlying this hesitation is trust. This review examines the determinants of consumer acceptance of AI-driven healthcare applications and digital therapeutics. It aims to synthesize evidence from consumer behavior, health informatics, and digital health literature to identify factors that promote or hinder adoption. A scoping review was conducted following the PRISMA 2020 guidelines. Relevant studies published between 2018 and 2025 were identified through Scopus, Web of Science, PubMed, and Google Scholar. The review was guided by established theoretical frameworks, including the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Risk Perception and Trust Theory. Consumer trust increases when AI systems are perceived as useful, easy to use, transparent, and capable of protecting personal health data. Conversely, trust declines when concerns arise regarding privacy, algorithmic opacity, and the absence of human oversight. Demographic factors such as age, gender, culture, and digital literacy significantly influence trust formation and adoption behavior. Physician recommendations, user reviews, and media endorsements also shape consumer perceptions. The successful adoption of AI healthcare technologies depends on trust-centered design, transparent data practices, clinician involvement, and culturally sensitive implementation strategies.

Keywords: AI-driven healthcare, Consumer trust, Digital therapeutics, Healthcare marketing, Personalized medicine, Purchase intention, Technology adoption.

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INTRODUCTION

Background of AI in Healthcare

A quiet healthcare revolution is taking place, largely out of sight to patients. Beneath the many layers of hospital information systems, insurance claims platforms and consumer health and wellness applications, artificial intelligence algorithms are reviewing data, looking for danger signs, proposing diagnoses and treatments, far faster and more efficiently than any human medical team ever could. The worldwide market for AI in healthcare was worth USD14.92 billion in 2024. In 2030, it is forecast to surpass USD110 billion an almost eight-fold increase in just six years (*Artificial Intelligence in Healthcare Market Report 2025-2030, By Offering, Function, and Geo*, n.d.).

This is occurring with real demand. Healthcare systems across the globe are suffering from an overwhelming abundance of patients. Over 75 million Americans do not even have access to primary care providers and the average wait time in the US for a specialist appointment is 59 days (*AI in Healthcare 2025 Statistics: Market Size, Adoption, Impact*, n.d.). Tools powered by AI promise to bridge that divide offering tailored advice, coaching and interventions without even needing to go to the doctor. As of May 2025, the Food and Drug Administration had approved 950 medical devices with AI incorporated into them the majority of which falling within radiology (Abràmoff *et al.*, 2020, 2022).

But the technology isn't enough in and of itself. These tools have to be used to be beneficial. And this is where it gets tricky. In April of 2024, polls found that 8/10 Americans thought some AI use in medicine might be beneficial, but 6/10 were uncomfortable with the idea of being diagnosed or treated by the technology (Vaassen, 2022). By May of 2025, acceptance had fallen from 52% to 42%

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not because the American publics lowered their expectations for AI, but because they were considering it more closely. This review will explore and attempt to understand the barriers to AI acceptance that accounts for this hesitancy and how we can mitigate the barriers so people are willing to use the tools when they are ready (Habib *et al.*, 2021; Obermeyer *et al.*, 2019).

Evolution of Digital Therapeutics

Digital Therapeutics (DTx) is a fairly new emerging class of healthcare product somewhere in between a wellness app and prescription medication. Digital therapeutics are defined as a software that has been demonstrated in clinical trials to treat, manage or prevent a disease. Unlike a fitness tracker or meditation app, digital therapeutics need to be proven in clinical trials to make any claims about health effects. Some digital therapeutics are prescribed by a doctor, and others are OTC (Kario *et al.*, 2022a; Sverdlov *et al.*, 2018a).

The case studies are becoming more compelling. A video game called Endeavor Rx (developed by Akili Interactive) was approved by the FDA to help with attention issues in children with ADHD. Pear Therapeutics created reset a prescribable digital therapeutic for substance use disorder. Somryst prescribes cognitive behavioral therapy for chronic insomnia. The digital health industry ($312.9B in 2024) is estimated to grow to $2.19T in 2034, at a rate of 21.2% per year (Makin, 2019a; Rassi-Cruz *et al.*, 2022a).

For DTx to realize this promise, the entire chain from awareness to adoption to ongoing usage has to function at each step. Consumers need to find out about the product, be confident it will benefit them, have confidence in the platform so they will provide their health data, make the decision to buy, use it reliably, and experience benefit. This review identifies the factors that facilitate or hinder each of those steps, focusing especially on how much trust matters (Biskupiak *et al.*, 2024a; Huh *et al.*, 2022a).

Importance of Consumer Trust in Healthcare Technology

Trust is easy to understand in the context of a doctor-patient relationship. As time passes you gain faith that your doctor is good at what he does; that he‘s acting in your best interest; that he will be truthful with you, even when the truth is not so pleasant. Now think about what happens when the ‘doctor’ is actually an algorithm. It can‘t look you in the eye. It can‘t talks you through its reasoning in simple language. It may even have been trained on data that did not include somebody like you. And if you get it wrong, who are you gonna sue? (Colloud *et al.*, 2023a; Tang *et al.*, 2024a).

And a more recent 2025 systematic review in npj Digital Medicine of 49 papers on trust in digital healthcare concluded that consumer trust in digital healthcare is influenced by multiple factors such as extent of human involvement, quality of data collection and storage, control by users over their data and even socioeconomic status including income, education. What the review showed is that “trust is not an end-state, but a characteristic that develops and degrades as a user interacts with a given platform…Over time, from entrance to exit pages, through the fifteenth week of implementation,” (Cummins and Schuller, 2020a).

The stakes are high. When individuals lack confidence in a digital health platform, they do not report their data truthfully, they drop out prematurely, and worst of all they sometimes make poorer health choices by replacing real clinical care with illicit AI content. A Gallup poll from 2025 indicated that by then 14 million Americans had already avoided a doctor visit completely by acting on a recommendation from an AI system that was a troubling indication of substitution behavior arising from undercalibrated confidence (*Der*, n.d.).

There are four aims to the review. One, to outline the key theoretical models that account for the formation of trust and purchase intention in technology-mediated healthcare; Two, to integrate the findings of recent empirical research on the relative importance of these factors; three, to investigate the moderating role of demographic and cultural context in altering the trust story for different populations; and four, to develop practice implications for developers, marketers, regulators and prescribers (Figures 1-3).

Conceptual Understanding

Consumer Behavior Theory in Healthcare

Researchers interested in consumer behavior have been working for decades trying to understand why people buy the things they do. Most of their work has been based on comparatively simple decisions: which brand of cereal to purchase, which new car to test drive. Healthcare decisions are different in fundamental ways. The consequences of getting it wrong are serious, even irreversible. The information disparity between the consumer and the practitioner is immense and the stakes of health and illness mean that rational cost-benefit calculations are rarely the whole story. In healthcare, involvement the extent to which a decision is personally relevant is always high (e.g. Managing a chronic illness or selecting a diagnostic technology). When the involvement level is high, consumers are more reliant on trust, perceived risk and social norm. This explains why trust is a prominent variable in AIPH adoption: the high stakes results in increased sensitivity to any signal of product failure or harm (Bauer *et al.*, 2013; Wood and Schulman, 2019).

Technology Acceptance Model (TAM)

The Technology Acceptance Model was developed by Fred Davis in 1989, and it is regarded as being the most utilized model of predicting user acceptance of a new information system. It is based on two fundamental assumptions: that individuals will use technology if they find it useful (Perceived Usefulness) and that they find using the technology easy (Perceived Ease of Use). These form together to create behavioral intention which then influences use (Calvo-Porral and Lévy-Mangin, 2014; Chivu *et al.*, 2021). The counterpart to this in AI health care is 'Help me really get healthier or my health care experience', for Perceived Usefulness; and 'Is this going to be hard to learn, and cheat me?' for Perceived Ease of Use. Both are important, but neither is enough on their own. A 2024 systematic review on mHealth app acceptance, while confirming TAM's core constructs was a good indicator of acceptance, claimed that data security and consumer trust should be added as the original model was designed for a pre-breached health data world. More comprehensive (e.g., TAM+ or "TAMminus Health") models of TAM are now frequently used, and include trust, privacy concerns, social influence, and health-specific beliefs as antecedents to TAM variables.7 This is necessary because, in health contexts, affect and relationship considerations impact, proportionally, as much as functional notions (AŞKUN *et al.*, 2021; Chivu *et al.*, 2021).

Theory of Planned Behavior (TPB)

Icek Ajzen's Theory of Planned Behavior introduces an important new aspect that is absent from TAM, which is social norms. TPB argues that individuals' actions are determined by three factors: their attitude to the behavior (is this a good idea?), the subjective norm (do those people I find like and respect do this and expect me to follow?), and their perceived behavioral control (do I feel I will be able to?). This framework is also illuminative of what two researchers have consistently found in their data on AI healthcare adoption: physician recommendation is the single strongest predictor of digital therapeutic adoption, explaining up to 41% of the variance in adoption intention (Elfiondri *et al.*, 2021). This is a subjective norm effect the behavior is deemed appropriate in part because an authority figure has recommended it. Conversely, it also describes why the social proof from patient communities on the internet influences decision-making so heavily, as well as why cost and subscription complexity influence adoption so heavily (Amrouche *et al.*, 2014; Tappy and Mandagi, 2025).

Perceived Risk and Trust Theory

Perceived risk is defined as the "consumer's subjective assessment of the probability that a selected product will have a potentially undesirable consequence". The main types of risk, as motivated in digital health, are performance risk (What if the AI provides me with the wrong answer), privacy risk (What if my health data is abused?), psychological risk (What if I feel less in control of my health through using the AI?) and financial risk (What if I purchase the service and it doesn't work?) (De Wulf *et al.*, 2005; Geyskens *et al.*, 2010). Trust is the mechanism that brings perceived risk to a level where action can happen. According to Mayer, Davis and Schoorman, trust is based on three pillars the ability of the entity being trusted to fulfill its expectations, benevolence of the trustor's perceived intentionality toward the trustor, and integrity of the trustor based on the perception that their intention is adherent to a set of moral and ethical principles (Liao and Xiao, 2025). As all three perceptions are high, trust is willing to be given. When any one perception is low, trust erodes; whether it be current aspirations of an algorithm as being reliable, current motives of an organization to monetize a data set over protect patients, or current transparency of the terms and conditions in a proposal or piece of legislation, trust erodes and, with it, the willingness to embrace (Ali, 2021; Steenkamp and Geyskens, 2014).

AI-Driven Personalized Healthcare

Definition and Scope

Personalized medicine has been a holy grail of medicine powerfully true and quite distant at the same time. What AI offers in this realm is the ability to actually do personalized medicine at scale. By learning from vast amounts of genomics data, electronic health records, wearables information, behavior profiles, and treatment results, AI can discover signals so subtle that no clinician can notice them, and can turn those signals into recommendations that truly differ from patient to patient (Cristini and Laurini, 2017; Hiu *et al.*, 2001).

The potential of AI-based personalized medicine is enormous. For example, AI programs that analyze a patient 's genetic profile to determine targeted treatments for cancer, algorithms predicting the likelihood of an individual returning to hospital within 30 days of discharge, tailored mental health support chatbots, and wearable technology that tracks physiological signals and warns either the user or clinician of any abnormality (Rezaei, 2015; Shim and Koh, 1997).

Types of Personalized Healthcare Technologies

I find it helpful to think of the various AIPH technologies in a handful of broad categories. Diagnostic AI operates predominantly in the background: it interprets medical images, test results, or genomic information to better detect disease at an earlier or more precise stage of progression. The FDA had approved 950 such AI-enabled devices by 2019, radiology is the most developed subsection (Antonić *et al.*, 2020; SPROLES and SPROLES, 1990). Predictive analytics tools leverage patient data to estimate who will need care, when it will be needed most, and in what form. Conversational AI chatbots and virtual health agents offer personalized advice, direction and emotional support on demand, every day. Wearable AI hardware plus machine learning produce individualized insights from constant collection of your body's biophysical data; and digital therapeutics (discussed in detail in Section 4) are their own, intriguing category requiring direct effort on the part of the end user (Hafstrom *et al.*, 1992; Walsh *et al.*, 2001).

Consumer Interaction with AI Systems

What distinguishes the adoption of AIPH from the adoption of most other technologies is the fact that the interaction is close and meaningful. When a consumer accesses an AIPH system, it is usually under a state of distress about a symptom, in the process of managing a chronic disease or convalescing. The emotional tonality of that interaction is thus critically important for trust development (Pindus and Hafford, 2019; Sprotles and Kendall, 1986). There is also research has been found a phenomenon identified by researchers as 'human-in-the-loop assurance'. Consumers are much more willing to follow an AI recommendation if they know it is checked or approved by a clinician. This indicates that the most trusted AI-powered health systems are not the ones replacing clinical judgment, but the ones making clinical judgment more predictable and more efficient. For healthcare organizations building AIPH platforms, this point has an obvious implication in practice: human oversight is not only a regulatory safetynet but also a trust architecture feature. Conversational AI systems encounter a specific calibration issue when considering perceived personality and affect. Research indicates that overly human sounding chatbots can feel unnatural and evoke feelings of manipulation or deception, whereas an overly robotic agent isn't capable of forming any kind of emotional connection with the user. The sweet spot is honest about the AI aspect, while still warm, emotive, responsive and helpful. Which, as it turns out, is a lot easier said than done, and is still an ongoing area of both research and product development (Czeczotko *et al.*, 2022; Wang *et al.*, 2018).

Digital Therapeutics and Consumer Adoption

Overview of Digital Therapeutics

Digital therapeutics carves out a strange middle ground. They are more scientifically rigorous than wellness applications in that they need to show clinical efficacy in peer-reviewed trials before even claiming a therapeutic benefit. But they are less well known than medications, and many patients and physicians alike remain uncertain how to conceptualize software as treatment. The DTx market is expanding at about a 25% annual clip due to increased insurance reimbursement, streamlining of the regulatory pathway, and a post-COVID up-tick in demand for remote and virtual care (Pearson *et al.*, 2023). The value proposition of the DTx is powerful: a tool that is always available, never has scheduling conflicts, does not involve travel, can be dynamically individualized based on data, and costs a tenth of an in-person clinical visit. The challenge will be to convince consumers who tend to think about treatment as a physical thing a pill, an injection, a procedure and who have good reason to be wary of tech companies promising clinical result (Phan *et al.*, 2023a; Rajendran *et al.*, 2024a).

Consumer Awareness and Perception

The most consistent finding in DTx market research is how low awareness remains outside of tech-savvy demographic segments. Surveys conducted across North America and Western Europe find that fewer than 30% of patients are aware that prescription digital therapeutics exist as a distinct regulatory category(Bohr and Memarzadeh, 2020; Shah and Shah, 2023). Among healthcare providers, the numbers are better but still concerning: many clinicians are aware that health apps exist but are uncertain which ones have been clinically validated and which are simply consumer wellness products with marketing language borrowed from the medical world (Digital Therapeutics (DTx): Everything You Need to Know, n.d.; Fietta *et al.*, 2025).

Among people who are aware of DTx, perceptions tend to split along condition lines. Digital therapeutics for mental health depression, anxiety, insomnia, ADHD face a dual stigma barrier. There is the general stigma around mental health treatment, and there is the additional skepticism that 'an app' could address conditions that even conventional medications struggle to fully resolve. DTx for metabolic conditions diabetes management, weight management face less of this skepticism, partly because the culture of health self-monitoring is already well-established in these communities through continuous glucose monitors and fitness trackers (Fietta *et al.*, 2025; Recchia *et al.*, 2020).

Factors Affecting Adoption Intention

The evidence from adoption research consistently points to five key factors. The first is perceived clinical efficacy the belief that the software will produce a real health improvement. This is distinct from trust in the company or the platform; it is about the core therapeutic claim, and it is largely built through communication of clinical evidence. Peer-reviewed publications, clinical trial result summaries, and testimonials from patients who experienced benefit all contribute to efficacy perception (Alexander *et al.*, 2020; Wiecek *et al.*, 2020).

The second factor and the single most powerful one identified in the literature is clinician recommendation. Consumer Trust in AI-Based Healthcare. A trusted Physician who states 'I think this will benefit you and you should try it', has a profound effect on intention to adopt, explaining 34-41% of the variance in a review across studies (Rowland *et al.*, 2020). But it also has huge implications for DTx marketing: resources aimed at clinician education and prescribing assistance may yield higher ads ROI than equivalent amounts spent on consumer media. The third is cost and coverage. Out-of-pocket expenses for DTx products can vary quite a bit those that are not covered by insurance will leave out quite a few consumers, especially lower-income groups, which tend to have the highest chronic disease burdens. The fourth is onboarding experience: how important is it that users, when they first open up the app for the first time, love it? Registration that is hard to complete, or no clarity on why they should use the app, or a not-super-fun first session will predict a user who abandons you swiftly. And the fifth is social proof reviews, ratings, patient community chats, and "word of mouth" that inform would-be users that others like them found it helpful (Metcalf *et al*., 2019; Phan *et al*., 2023b).

Trust Formation Mechanisms

Trust seems not to be present all at once. Instead trust develops in stages, beginning from the first time someone encounters the product or indeed a product of its kind its name, its logo, its description in an app store, a friend's recommendation and carries on with each encounter. Researchers categorise the concept of trust by differentiating initial trust (which develops before any interaction with an artifact) and ongoing trust (which develops as a result of interaction) (Luderer *et al*., 2022; Wang *et al*., 2023).

Brand signals--institutional affiliations (is this endorsed by an accepted hospital or university?), regulatory approvals (was this FDA approved?), and the institutional affiliations and other brand signals (who else is actively recommending this?) play a key initial role in building trust in AI health systems. A 2025 rapid review of trust in the use of AI in healthcare identified 4 mechanisms for the building of trust over longer periods of use--transparency (can the system reveal to me what it is trying to do and why?), accountability (is there anyone to blame if things go wrong?), human input (is there a clinician stakeholder in this?) and empowerment (does this make me feel less competent or more?) (Ramakrishnan *et al*., 2021). These four features, by the way, are not optional. They constitute the architecture of a trustworthy relationship and have to be designed into the product carefully. An AI health app that produces a personalized risk score based on nothing that can be explained, where nothing can be done about when something goes wrong, where the user can never consult a clinician, that pushes advice in a way that actually disempowers rather than empowers, that app will not be used, no matter how accurate the model behind it is (Rassi-Cruz *et al*., 2022b; Yan *et al*., 2021).

Data Privacy and Security Concerns

If there is one conclusion that resonates the most in the consumer trust and AI health literature, it is that customers are deeply concerned about their data. In a 2024 survey of over 1,000 U.S. consumers, 82% responded that AI data loss-of-control was a very serious personal concern, with 43% indicating that it was 'very serious'. 81% responded that they believed their companies were using their personal data to train AI without revealing it. 18% of respondents believed AI data handling was not a serious concern (Valentine *et al*., 2020; Whaley *et al*., 2019). These worries are not unfounded. Medical records are arguably some of the most sensitive information a person can have. Data about health can convey lifetime medical histories, mood records, drug usage, reproductive preferences, genetic susceptibilities, and a host of other information (Amisha *et al*., 2019; Farhud and Zokaei, 2021). A health record breach isn't like a credit card breach-you can't just cancel your genome. And profit-generating incentives of tech giants, whose business models are based upon harvesting and selling data, create a genuine and important conflict of interest with patients who want personal health information private (Block *et al*., 2015; Goodman *et al*., 2022; Mennin *et al*., 2013).

These frameworks are also complicated by the fact that they are changing quickly. In the European Union, the new EU AI Act (2024) and the previously established GDPR (2018) lay out a risk considered-based governance regime for clinical tools, with the highest requirement threshold being applied at the highest risks (Dang *et al*., 2020). In the US, HIPAA establishes basic protections for health information, but while it applies to some consumer health apps it does not apply to providers or developers that are not covered entities, leaving consumer health applications in a regulatory gray area (Graham *et al*., 2019). For consumers, the question simply becomeswho has my health data, whathappens to it, andwhat can I do to change it? (Ellahham, 2020; Lee *et al*., 2021).

Transparency and Explainability

What is the technical term for the transparency problem of AI? It is known as the black box problem where there are several extremely sophisticated AI models especially deep neural networks that gain their predictive power through processes that are, ironically, unimaginably inscrutable, even to the engineers who constructed them. They take in millions of data points, apply weights that are nearly impossible to track, and produce an end result. It may be right, but it can't be understood (Keefe *et al*., 2022; Tang *et al*., 2024b).

For consumers this lack of transparency creates trust issues. When a clinician recommends a treatment a patient can readily ask 'why?' and be given an answer they can assess. When an AI system generates a risk score or treatment recommendation and has not indicated why a consumer cannot ask why. They are in a position of having to trust blindly or not at all and most choices not to place blind trust (Cummins and Schuller, 2020b; Huh *et al*., 2022b).

Explainable Artificial Intelligence (XAI) methods, such as those that identify the data points that most contributed to an end prediction, are increasingly being integrated into the interfaces of health care AI systems. Studies suggest that even simple, plain-language explanations ("Your cardiovascular risk estimate is elevated primarily because of your age,(Markose *et al*., 2016; Nordling, 2019) blood pressure readings over the last 6 months and your family history") significantly increase consumer trust in AI health advice over informationless returns, despite identical underlying predictions. Explanation need not be complete algorithms, it need only be enough transparency to respect

Table 1: Summary of Core Theoretical Frameworks Applied to Consumer Trust in AI Healthcare.

Framework	Core Constructs	How It Applies to AI Healthcare	Key Limitation in This Context
Technology Acceptance Model (TAM) Davis, 1989	Perceived Usefulness (PU); Perceived Ease of Use (PEoU); Behavioral Intention.	Explains why consumers adopt or reject AI health tools based on functional value and usability perceptions.	Does not natively account for trust, privacy risk, or emotional dimensions of health decisions.
Theory of Planned Behavior (TPB) Ajzen, 1991	Attitude; Subjective Norm; Perceived Behavioral Control; Behavioral Intention.	Explains the strong influence of physician recommendation and peer norms on DTx adoption.	Attitude formation mechanisms in AI contexts are not fully specified.
Perceived Risk Theory Jacoby & Kaplan, 1972	Performance risk; Privacy risk; Financial risk; Psychological risk; Social risk.	Maps the specific fears (data misuse, AI error, loss of autonomy) that prevent adoption.	Does not specify which risk type dominates across different health conditions or populations.
Trust Theory Mayer, Davis & Schoorman, 1995	Ability; Benevolence; Integrity; Willingness to be vulnerable.	Explains how consumers calibrate trust in AI systems that replace or augment clinical judgment.	Built on interpersonal trust; transferring to algorithm-based systems requires conceptual extension.
Extended TAM / TAM+ (Multiple authors, 2015-2025)	TAM constructs + Trust + Privacy concerns + Social influence + Health-specific beliefs.	Most comprehensive predictor of AI health tool adoption; validated in multiple digital health contexts.	Model complexity increases with each extension; parsimony and cross-cultural replication remain challenges.

consumers as informed partners in their medical care (Kario *et al.*, 2022b; Makin, 2019b).

Ethical Concerns in AI Healthcare

In addition to privacy and transparency, I have also cited a growing literature documenting a disturbing trend: as a general rule, AI health systems can be systematically less accurate for some groups of patients than others. This is the algorithmic bias issue, and it is especially significant in health care given the fact that unequal AI outcomes will result in unequal health care outcomes (Hong *et al.*, 2021). For example, there have been studies documenting performance inequities based on race in dermatology AI, pulse oximetry algorithms, and cardiovascular risk prediction models all three where the relevant AI system was trained on data that over-represented certain populations (Rassi-Cruz *et al.*, 2022c; Sverdlov *et al.*, 2018b).

From a trust in the consumer angle however the implications are also quite profound. Communities already-historicall y-discriminated-against in healthcare and with the most reason for skepticism in newly-designed technologies from predominantly white, middle/upper-class, technology-oriented companies face additional relatively-well-justified trust issues when it comes to their use of AIPH tools (Rajendran *et al.*, 2024b). Good products alone are not enough in order to get communities to trust AIPH products, a demonstrated commitment to fair design practices, an open audit of algorithm performance by diverse groups, and the incorporation of diverse voices into product development and testing (Biskupiak *et al.*, 2024b; Colloud *et al.*, 2023b).

Psychological Factors Influencing Purchase Intention

Perceived Usefulness and Outcome Expectancy

Central to every consumer‘s decision to adopt an AI health tool is this straightforward question: “is this actually going to help me?” Perceived usefulness is a consumer‘s post-adoption belief that using an AI health solution will enhance their health or care experience. Consumers base this belief on a set of factors that include clinical evidence (where available and understandable), experience with other similar tools, anecdotal recommendations from either other consumers or clinicians, and reputation of the organization behind the product (Davenport *et al.*, 2020; Perez-Vega *et al.*, 2021).

Perceived usefulness for AI healthcare tools has an interesting twist: the personalization promise. An AI tool that promises to give you recommendations tailored to your data inherently claims to be of higher use than general reference points or broad recommendations. This promise of personalization set high hopes for changes in usefulness. When the enhancement turns out to be truly helpful, users become satisfied and loyal. When it turns out that the AI does nothing more than offering the same advice in different words, users are rapidly disappointed and lose trust more quickly than they would not have had all along had they not been in the first place (Poushneh, 2021; Rasheed *et al.*, 2023).

Ease of Use and Health Literacy

Health literacy, which is defined as ‘the ability to find, understand, evaluate and act upon health information’ is a relatively unexamined variable in digital health usage (Lalicic and Weismayer, 2021). An estimated 36% of adults in the U.S. have low health literacy, with even higher prevalence among the elderly, lower income individuals, and those with lower levels of education (Gomes *et al*., 2025). Users with low health literacy will experience the perceived ease of use of an AI health intervention differently, as it is a construct that depends both on the interface of the system and the systems health concepts that it aims to communicate (Moriuchi, 2021; Taghikhah *et al*., 2021).

The paradox is that those who need health support the most are often the ones most unable to use AI health tools. Registration

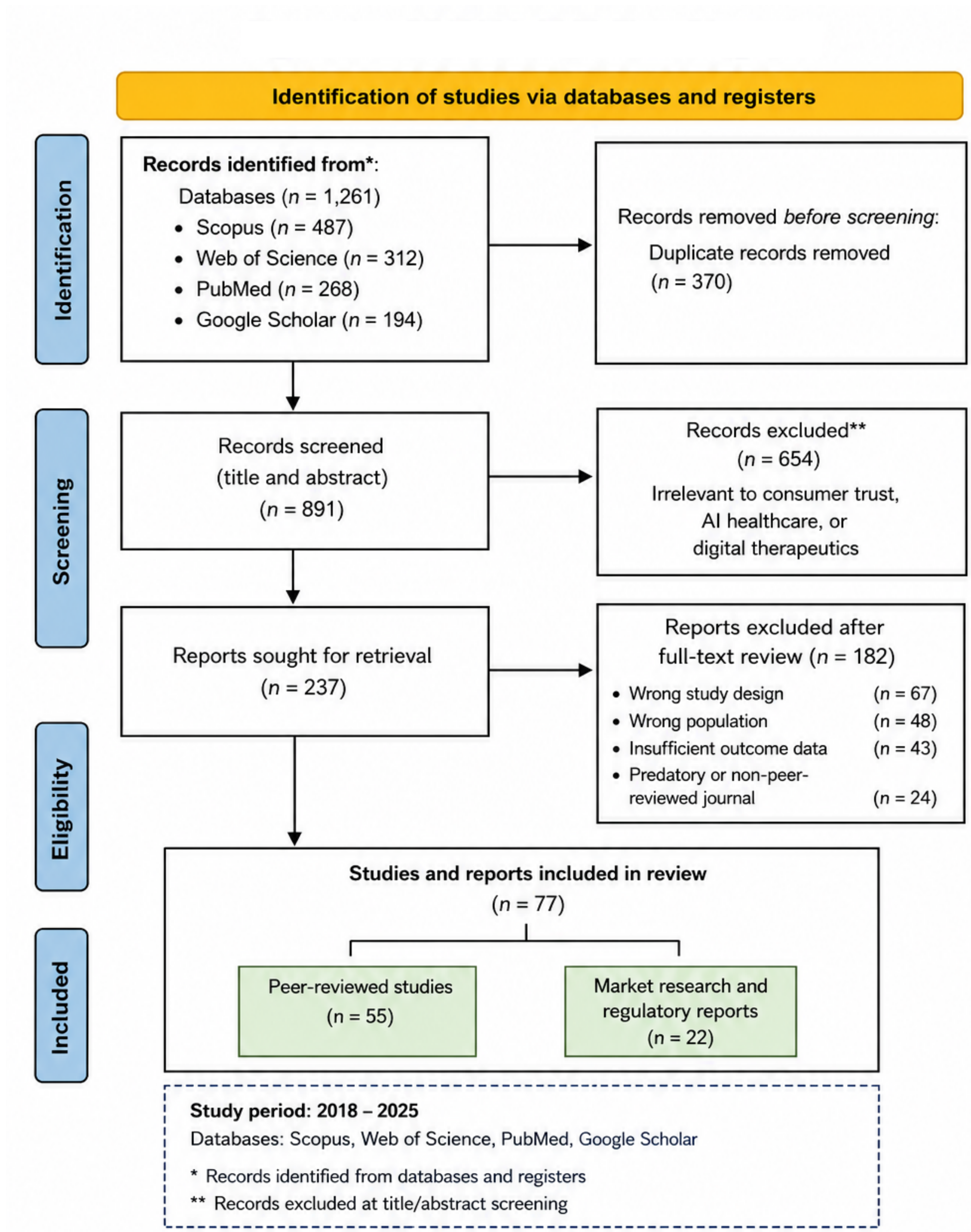

Figure 1: PRISMA 2020 Flow Diagram Literature Identification, Screening, Eligibility, and Inclusion. Records were identified from Scopus (n=487), Web of Science (n=312), PubMed (n=268), and Google Scholar (n=194). After removal of duplicates, 891 unique records were screened at the title and abstract level. Of these, 654 were excluded as irrelevant to consumer trust, AI healthcare, or digital therapeutics. Full-text review of 237 records resulted in a further 182 exclusions (wrong study design, n=67; wrong population, n=48; insufficient outcome data, n=43; predatory or non-peer-reviewed journal, n=24). Final inclusion: 55 peer-reviewed studies plus 22 market research and regulatory reports. Study period: 2018-2025.

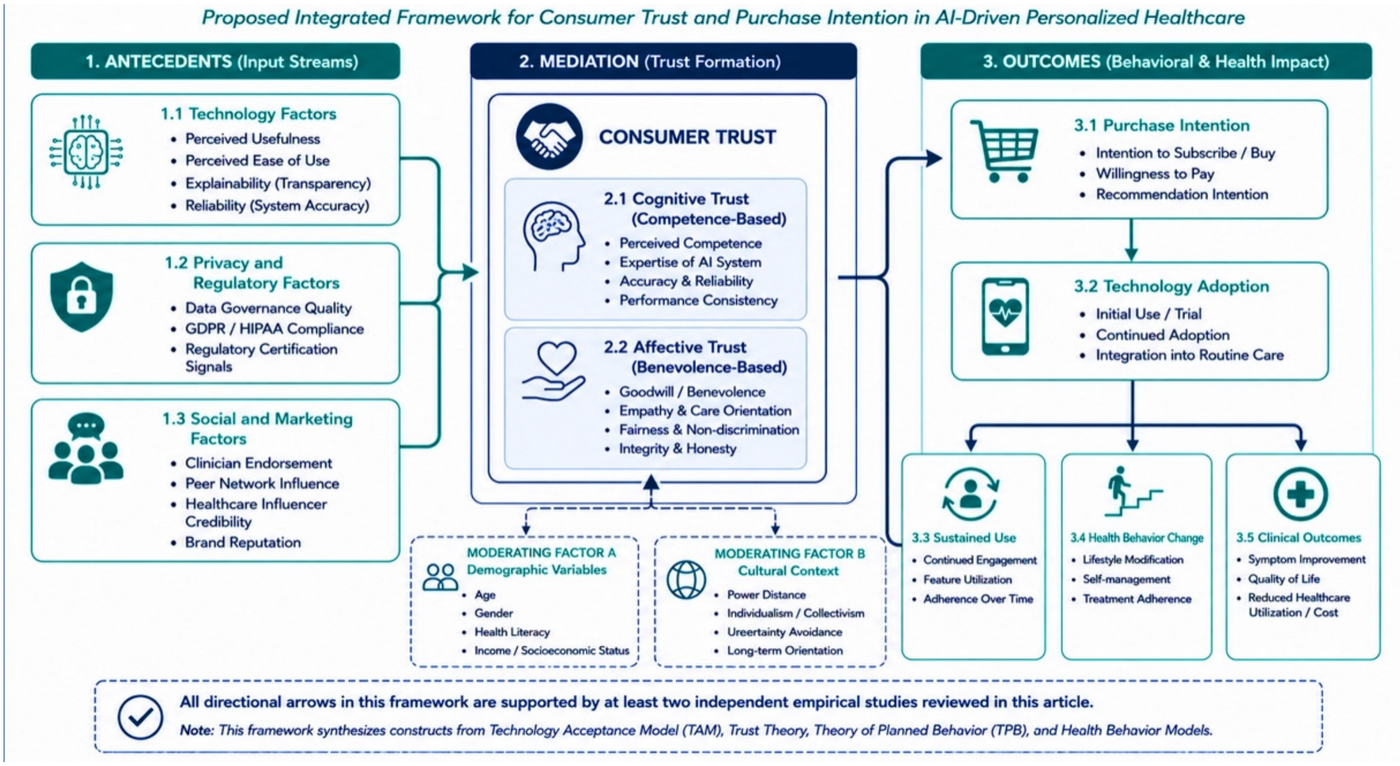

Figure 2: Proposed Integrated Framework for Consumer Trust and Purchase Intention in AI-Driven Personalized Healthcare. The framework illustrates three sequential domains. Left panel Antecedents: three input streams feed into trust formation: (1) Technology Factors perceived usefulness, perceived ease of use, explainability, reliability; (2) Privacy and Regulatory Factors data governance quality, GDPR/HIPAA compliance, regulatory certification signals; (3) Social and Marketing Factors clinician endorsement, peer network influence, healthcare influencer credibility, brand reputation. Center panel Mediation: Consumer Trust (subdivided into Cognitive Trust [competence-based] and Affective Trust [benevolence-based]), moderated by Demographic Variables (age, gender, health literacy, income) and Cultural Context (power distance, individualism/collectivism). Right panel Outcomes: Purchase Intention leading to Technology Adoption, which in turn predicts Sustained Use, Health Behavior Change, and Clinical Outcomes. All directional arrows are supported by at least two independent empirical studies reviewed in this article.

systems so complex that they rival a passport application, technology written in inaccessible medicalese on and in-app, and AI reports that speak to an extraordinary level of health literacy all serve as friction that places more barriers in front of disadvantaged still more disadvantaged groups of people(Grewal *et al*., 2021; Park *et al*., 2021). Designing for the user with the most barriers not the most technological literacy is both a moral and a business imperative in AI healthcare (Abrardi *et al*., 2022; Chintalapati and Pandey, 2022).

Emotional Engagement

Health is not a neutral subject. People fear illness, cling to their perceptions of bodily identity, are passionately concerned for others, are sometimes in denial, and so on. Any healthseeking AI that simply sees the user as a nonemotional, purely rational agent fed with information is going to fail to tap into most of what actually motivates or inhibits their behaviour (Jahn, 2011; Marcus, 2018).

The degree to which digital therapeutics foster emotional engagement hinges greatly on whether users feel understood as a person. Across DTx, this is achieved through such features as personalized check-ins referencing personal history and preferences, visualizations of ongoing progress that feel tangible and satisfying, and perhaps paradoxically, the ability to acknowledge and validate the experience of negative emotions rather than steer relentlessly toward positive ones. Clinically equivalent DTx platforms exhibiting such features demonstrate significantly greater adherence and retention than purely utilitarian interfaces (Atwal and Bryson, 2021; Ribeiro *et al*., 2025).

Social Influence and Peer Recommendation

The most consistent finding from the studies on AI adoption in healthcare is that patients are deeply swayed by the choices and recommendations of other individuals whom they trust. Clearly, this amounts to social influence and works hand-in-glove at various levels (Doraiswamy *et al*., 2019; Lopes *et al*., 2025).

On an institutional level, clinician recommendation, as noted, is the most effective external signal for DTx adoption. At a community level, the banter and peer pressure made possible by online patient communities, health groups on social media, and the proliferation of condition area online forums establish informal information spheres in which users exchange their own digital health tool usage experiences in ways likely to induce either significant adoption waves or significant avoidance waves (Murphy *et al*., 2021; Su *et al*., 2025). An individual with diabetes receiving fifteen other social group's members who shared use of a blood sugar managing application would be a stark contrast to the company's marketing shine (Arora *et al.*, 2021; Kaye *et al.*, 2020).

Role of Digital Marketing and Social Media

Healthcare Influencer Marketing

Social media has found a new niche with this group of healthcare communicators: the physician-influencer, or PhInfluencer. These are our licensed providers, sometimes one-in-the-hundreds-of-thousands strong, who communicate health messages, review testkits/products, comment on healthcare innovations, and build public trust in their individual professional judgment through Instagram, TikTok, YouTube, and LinkedIn (Culnane *et al.*, 2017; Mennella *et al.*, 2024). For AI health companies, an endorsement by a responsible physician-influencer may have greater standing than a traditional advertisement cementing the product with institutional like-ability (author has M.D. and hands-on experience) paired with individual like-ability (using your voice to express your opinions) (Ghufran and Ahmad, 2025; Zhang *et al.*, 2021).

The ethical complexity of influencer healthcare marketing is genuine; paid affiliations are not sufficiently disclosed, especially by nonclinician influencers marketing health products to broad audience bases. Hyped claims of efficacy that attribute unreasonable clinical outcomes without sufficient evidence are prevalent enough that authorities in the US and EU. have published joint guidance on social media health marketing. To consumers, this means that the same social media environment that can spread news of effective health interventions can proliferate unfounded ones (Pröbster *et al.*, 2025; Tayebi and Garibay, 2025).

Online Reviews and Consumer Confidence

Before using a health app especially one that costs money or asks for any personally identifiable information most consumers want to know what other customers think. App store reviews, health informatics-oriented review sites, and pubic forum conversations serve as crowdsourced signals of quality in a market where authoritative information, like the results of clinical trials or clearance by regulators, is skewed and difficult to interpret (Kumar *et al.*, 2023; Vulli *et al.*, 2022). Studies of consumer responses to online reviews in health technology markets have discovered what might be called a credibility dilemma: if reviews about a technology are excessively positive they are viewed suspiciously and suspected to be fabricated; if reviews are too negative consumers lose faith in the sites usefulness without learning too much about what to expect from the technology. The most credible reviews provide diverse evidence, such as varied ages, conditions, and technology competence levels among the reviewers, and distinct positive and negative experiences with the product (Drzyzga, 2024; Johnson *et al.*, 2025).

Brand Reputation and Loyalty

In a market where performance evaluation is directly costly for the consumer most consumers are unable to independently determine whether or not an AI diagnostic algorithm is truly effective brand reputation acts as an important indicator of quality. Consumers tend to give disproportionate initial trust to AI health products tied to known healthcare institutions (large

Table 2: Categories of AI-Driven Personalized Healthcare Technologies and Associated Consumer Trust Dynamics.

Technology Category	Examples	Primary Consumer Benefit	Main Trust Barrier	Regulatory Status (2025)
Diagnostic AI (Imaging & Pathology)	IDx-DR; Aidoc; Google DeepMind (retinopathy).	Earlier, more accurate diagnosis without waiting for specialist appointment.	Black-box decisions; fear of misdiagnosis; unclear accountability.	FDA cleared; 76% of 950 AI devices are radiology-based.
Predictive Analytics Platforms	Health Catalyst; Livongo Risk Engine; IBM Watson Health.	Proactive identification of at-risk patients; personalized prevention.	Privacy concerns; distrust of algorithmic risk scores.	Regulated as Software as a Medical Device (SaMD).
Conversational AI / Chatbots	Woebot (mental health); Ada Health; Babylon	24/7 access; non-judgmental; condition-specific guidance.	Perceived lack of empathy; concern about over-reliance.	Class I/II SaMD; varies by claim made.
Wearable + AI Analytics	Apple Watch ECG; WHOOP; Oura Ring.	Continuous monitoring; personalized health insights; early warning.	Data ownership; who accesses the data; accuracy concerns.	FDA authorized for specific clinical claims only.
Digital Therapeutics (DTx)	EndeavorRx (ADHD); reSET (substance use); Somryst (insomnia).	Clinically validated treatment delivered via software.	Efficacy skepticism; prescription friction; adherence challenges.	FDA Breakthrough Device designation; Rx and OTC pathways.

Table 3: **Summary of Key Empirical Studies on Consumer Trust in AI-Driven Healthcare (2020-2025).**

Study / Source	Study Type & Context	Key Constructs Examined	Key Findings	Framework Used
Yap *et al.*, npj Digital Medicine (2025)	Systematic review; 49 studies; consumer + HCP perspectives.	Trust domains, privacy, human interaction, digital literacy, income.	Trust in digital health is multidimensional; shaped by human-in-loop degree, privacy, accuracy, and digital literacy; affects use, adoption, and perceived usefulness.	Narrative synthesis /integrative.
Stephens *et al.*, Digit Health (2025)	Qualitative systematic review; consumer perspectives on AI/ ML diagnostics.	Acceptance, transparency, oversight, autonomy.	Consumers accept AI diagnostics when clinician oversight is retained; transparency about AI limitations is essential for trust.	Inductive qualitative synthesis.
Bhagat & Shaikh, IJRT (2025)	Empirical; AI personalization and consumer trust survey.	AI personalization, perceived privacy risk, consumer trust, purchase intention.	Personalization raises privacy risk perceptions; consumer trust mediates the link between personalization and purchase intention; brands maintaining transparent data practices convert personalization benefits into loyalty.	Perceived Risk Theory + TAM
Relyance AI Consumer Survey (2024/25)	Descriptive survey; 1,000+ U.S. consumers.	AI data control perception, threat severity, willingness to pay premium.	82% see AI data loss as serious personal threat; 81% believe undisclosed AI training is occurring; 75%+ will pay premium for verified data governance.	Descriptive / survey
Tao *et al.*, Healthcare (2023)	Consumer survey; m-Health acceptance.	Self-determination theory, task-technology fit, TAM constructs.	Intrinsic motivation (autonomy, competence, relatedness) and task-technology fit improve TAM's predictive power for health app adoption.	Integrated SDT-TTF-TAM
Park *et al.*, J Med Internet Res (2024)	Mixed-methods; cancer survivors using health apps.	User experience, clinician recommendation, TAM, adherence.	Positive first-session user experience and clinician recommendation are the strongest predictors of sustained health app use among cancer patients.	Extended TAM + UX
Ohio State University / Gallup Survey (2025)	National U.S. population survey.	AI healthcare acceptance, trust trajectory, provider substitution behavior.	AI healthcare acceptance fell from 52% to 42% between 2024 and 2025; 14 million U.S. adults skipped a provider visit based solely on AI advice-indicating risky substitution behavior.	Descriptive survey

hospital systems, academic medical centers, familiar pharma companies) relative to new consumer tech competitors, even when the technology is equal (Byrne *et al.*, 2017; Social Media Influencers in Healthcare and Pharma: What's Their Role? | by Cyn Meyer | Medium, n.d.-a).

Brand loyalty in AIPH is therefore a little different than loyalty in standard consumer products; buyre-order relationship. This is because trust in a service is also a data-sharing relationship, where users who continue to trust the service keep contributing the personal health data which helps the AI adapt to be more personalized. Those who lose trust cease not only buying but supplying data which degrades the product for everyone else. Trust maintenance thus becomes a literal product quality requirement, not a brand marketing issue (Jeyaraman *et al.*, 2023a; Wati *et al.*, 2025).

Age and Technology Acceptance

Age is the most reliably reported demographic moderator of AI adoption in healthcare, and this is not surprising: older adults by and large have lower digital literacy, are less familiar with app-based services and would prefer interactions with human providers in healthcare context. In terms of TAM, both Perceived Usefulness and Perceived Ease of Use will, on average, be lower at baseline for older populations than for younger ones, even before specific concerns about safety or privacy feed into this (Alves *et al.*, 2019; Wong *et al.*, 2021a).

That said, age is not deterministic. The olderage chronic conditions utilizing active self-care diabetes, heart failure, COPD subjects on digital health are much, much more open to it than others for their age based on mean averages, as high perceived benefit (e.g. «good enough») outweighs high ease-of-use barriers. When worse health outcomes are just around the corner, motivation for digital health tools is much, much higher (Karim *et al.*, 2020a). The real lesson on AIPH for the designing team must be that technology should not discriminate against old people by expecting lives in which they are no longer able to handle innovative devices; old people are the workhorse that deal with the high disease burden and high potential health benefit (Chen and Wang, 2021a).

Gender-Based Consumer Behavior

Gender influence on AI health tech use relates to the type of condition, social expectations, and trust trends. Females exhibit higher levels of health information seeking behavior (across all media types) and more frequent utilization of mental health and wellness applications, reproductive health care applications, and patient support communities. Males are more active in the utilization of AI empowered performance analysis, sports

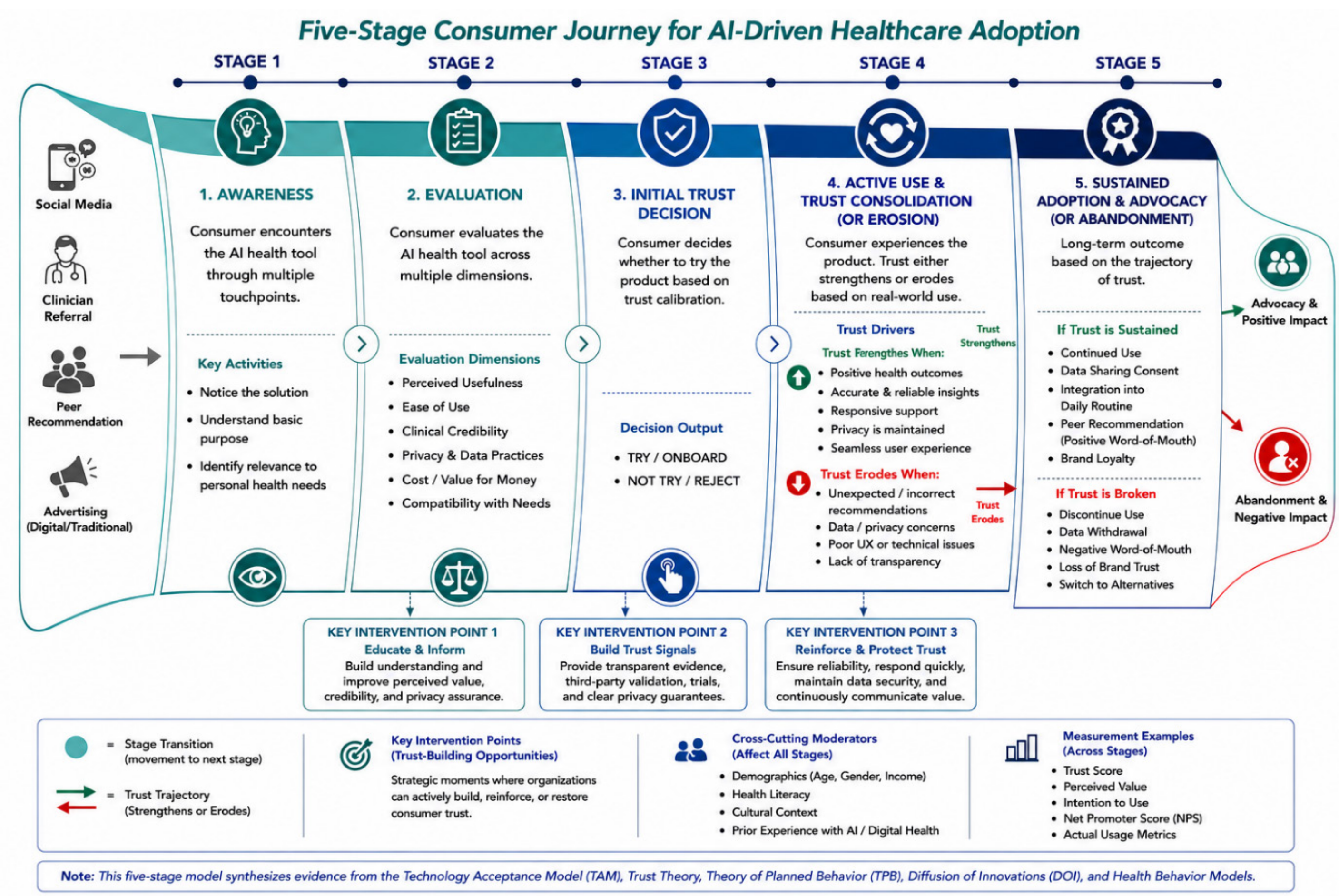

Figure 3: Five-Stage Consumer Journey Model for AI-Driven Healthcare Adoption. Stage 1- Awareness: consumer encounters the AI health tool through social media, clinician referral, peer recommendation, or advertising. Stage 2- Evaluation: consumer assesses perceived usefulness, ease of use, clinical credibility, privacy practices, and cost. Stage 3- Initial Trust Decision: consumer decides whether to try the product, based on trust calibration across all evaluated dimensions. Stage 4- Active Use and Trust Consolidation (or erosion): through actual product use, trust either strengthens (positive outcomes, responsive platform, privacy maintained) or erodes (unexpected recommendations, data concerns, poor UX). Stage 5 Sustained Adoption and Advocacy (or abandonment): sustained trust leads to continued use, data sharing, and peer recommendation; broken trust leads to abandonment and negative word-of-mouth. Key intervention points for trust-building strategies are shown at Stages 2, 3, and 4.

Table 4: Evidence-Based Recommendations for Key Stakeholders in AI-Driven Healthcare.

Stakeholder Group	Primary Challenge	Recommended Action	Evidence Basis
AI Health Platform Developers	Low consumer trust; high privacy anxiety undermining adoption.	Implement privacy-by-design; integrate plain-language XAI explanations; publish third-party algorithmic audits; make human oversight pathways visible to users.	Yap *et al.* 2025; Relyance Survey 2025
Digital Therapeutic Companies	Low consumer awareness; prescription dependency; early abandonment.	Invest in clinician prescribing support programs; develop patient ambassador networks; optimize onboarding for first-session retention; pursue insurance formulary inclusion.	Krebs & Duncan 2015; Sverdlov *et al.* 2018
Healthcare Marketers	Misinformation environment; influencer credibility risks.	Partner with credentialed physician-influencers; require full disclosure of commercial relationships; amplify patient testimonials tied to specific clinical outcomes; model honest communication of limitations.	Gabarron & Wynn 2016; Bhagat & Shaikh 2025
Policymakers and Regulators	Regulatory fragmentation; consumer protection gaps; innovation barriers.	Harmonize international SaMD classification; develop consumer-facing AI health certification marks; mandate demographic bias audits for high-risk clinical AI; establish clear wellness vs. medical device boundaries.	FDA 2025; EU AI Act 2024
Clinicians and Healthcare Providers	Limited DTx prescribing literacy; insufficient CME on digital health.	Integrate DTx into clinical education and residency training; develop validated prescribing decision support; create patient referral pathways; discuss AI tool use proactively in consultations.	Park *et al.* 2024; Krebs & Duncan 2015
Insurance Payers	DTx reimbursement uncertainty; insufficient real-world evidence.	Establish outcomes-based reimbursement frameworks tied to validated health metrics; support real-world evidence generation through coverage-wit h-evidence-development programs.	Sverdlov *et al.* 2018
Patient Advocacy Organizations	Consumer misinformation; health equity gaps in AIPH access.	Develop community-based AI health literacy programs; advocate for subsidized access and low-bandwidth design requirements; commission independent audits of AI product performance across demographic groups.	Obermeyer *et al.* 2019; Eysenbach *et al.* 2002

oriented health tracking, and cardiovascular health wearables (Latif *et al.*, 2019; Zotti *et al.*, 2019).

Women also have higher awareness of privacy risk online health and are more responsive to social influence cues than men. Effects of physician recommendation and peer endorsement on intentions to adopt are generally more positive for women than for men across studies. This is not gendered by nature, but tends to indicate that women have been more actively involved in the decision making of health care (for them and for their family) and more experienced in dealing with health systems (and their faults) (Abroms, 2019; Naslund *et al.*, 2020a).

Cross-Cultural Variations

One of the least examined areas within the results of this research on health trust in AI may be that of cultural differences. The bulk of the research most influential on current understanding comes from the United States, Western Europe, and increasingly China, leaving a huge portion of the world and diverse cultures unexamined (Suarez-Lledo and Alvarez-Galvez, 2021; Zamora, 2022a).

However, the limited cross-cultural evidence we have is of significant consequence. In high-power-distance cultures where power that institutional authorities are presumed to have is unquestioned, consumers are much more likely to accept health recommendations from AI when they are received from institutional authorities. In China, AI health advice from a known medical institution (compared to a tech company) was much more likely to be believed by consumer (D'Souza *et al.*, 2021). When consumers originate from low-power-distance Western cultures, they expect far more explanation, co-participation and visible proof of their choice-respecting autonomy (Naslund *et al.*, 2020b; Wong *et al.*, 2021b).

In collectivist cultural contexts, subjective norms tend to have greater influence on adoption adoption happens quickly when the use of a particular health app is considered normative in that culture. In individualist cultures, attitudes and perceived control matter more(Saenger *et al.*, 2018). Different as these two cultural types are, healthcare marketers creating a global AI health product launch strategy would do well not to ignore these differences; a message that builds trust in one culture can backfire in another (Bozzola *et al.*, 2022; Sutherland and Jalali, 2017).

Consumer trust and adoption of AI-driven healthcare vary across different demographic and cultural groups. Young adults (18-44 years) generally show a higher willingness to adopt AI healthcare technologies because they have greater digital literacy, are comfortable using mobile applications, and frequently obtain health information through social media. Therefore, developers should focus on innovative features, personalization, and user-friendly app experiences for this group (Tables 1-4).

Older adults (65 years and above) tend to have lower initial acceptance due to limited familiarity with digital technologies and perceived difficulty of use. However, those managing chronic diseases may be more willing to adopt AI healthcare tools if they perceive clear health benefits. For this population, simple interfaces, clinician recommendations, and integration with familiar health devices are important.

Female consumers are generally more concerned about data privacy and are more influenced by recommendations from healthcare professionals and peers. As a result, developers should emphasize data security measures, peer-review options, and clinician endorsements. Male consumers often show greater interest in innovative technologies and performance-tracking features, making outcome measurement and fitness-related applications particularly appealing.

Individuals with high health literacy are more likely to critically evaluate AI healthcare solutions and expect evidence-based information. Providing clinical evidence, transparent explanations of AI functionality, and access to personal data can improve trust among these users.

Cultural factors also influence adoption. In high-power-distance cultures, such as many East Asian countries, consumers are more likely to trust AI healthcare technologies when they are endorsed by respected institutions or authorities. In contrast, consumers in low-power-distance cultures, such as Western Europe and North America, prefer greater transparency, explanations of how AI works, and more control over their personal data. Therefore, explainable AI features and user-control options are particularly important in these regions.

Challenges and Barriers

Regulatory Uncertainty

For buyers seeking to assess whether an AI health product really is what it claims to be, 'Is this actually what it says it is?' turns out to be a vexingly complex question. The regulatory environment for AI health tools is difficult to untangle, ever-changing, and a challenge for practitioners outside the field to keep up with. But the U. S. Food and Drug Administration's (FDA) Software as a Medical Device (SaMD) designation offers one route for AI health tools that make concrete clinical claims, even while the distinction between a regulated medical device and an unregulated wellness app is regularly challenged and retested by enterprising companies seeking to avoid the regulatory burden and delays of a comprehensive review (Lambert *et al.*, 2012). The EU AI Act 2024 is the most comprehensive, risk-based regulatory framework ever proposed for AI systems the far rigid requirements would be imposed on AI systems that could have a 'meaningful impact' on people's health, safety or fundamental rights (a sphere that encompasses most clinical AI applications) (Karim *et al.*, 2020b; Kind, 2015). As well as offering greater protection for consumers and more certain compliance obligations for developers, the Act will also increase the costs and difficulty of gaining access to the EU market for DTx and AIPH products a potential problem for small developers who may be in a position to develop truly valuable innovations for neglected patient groups (Marshal *et al.*, 2021).

Misinformation and Consumer Skepticism

The digital channels that help make AI health tools available at scale to consumers can readily provide unhealthy information at scale as well. Social media algorithms are powered by maximizing engagement, not maximizing accuracy. Misinformation exaggerating the miraculousness of cures, catastrophizing the unseen dangers of known treatments, concocting conspiracy theories about drug companies is reliably more successful at finding its way into people's edges' feeds than sound health advice (Davis *et al.*, 2015; Schønning *et al.*, 2020).

For AI health product developers, the misinformation environment creates a hostile baseline. Consumers who have been exposed to exaggerated or false claims about AI healthcare capabilities and most consumers encounter some version of these claims regularly bring pre-formed skepticism to their evaluation of legitimate products. The practical response is not simply to make louder counter-claims but to model a different kind of communication: honest about uncertainty, transparent about limitations, specific rather than vague about clinical evidence, and willing to acknowledge what the product cannot do as readily as what it can (Chen and Wang, 2021b; Muhlen and Ohno-Machado, 2012).

Accessibility and the Digital Divide

AI health technology has an equity problem. The populations that stand to gain most from affordable, accessible, personalized health support people with high chronic disease burden, limited access to specialist care, and inadequate health system engagement are the same (Praveen *et al.*, 2022; Rajpurkar *et al.*, 2017) populations that face the greatest barriers to using AI health tools. Smartphone ownership, reliable broadband connectivity, and basic digital literacy are all prerequisites for most DTx and AIPH platform engagement, and all three are unequally distributed by income, age, geographic location, and education (Antheunis *et al.*, 2013; Peck, 2014).

In the United States, approximately 25% of adults over 65 do not own a smartphone. Twenty-one million Americans lack broadband internet access. Globally, these proportions are substantially higher. If AI health technology adoption follows the same pattern as previous digital health innovation providing the most benefits to the most advantaged users while leaving behind those with the greatest need the result will be a measurable increase in health inequality rather than the democratization of care that the technology's advocates promise (Jeyaraman *et al.*, 2023b; Zamora, 2022b). Addressing this requires deliberate design choices (low-bandwidth optimization, voice-based interfaces, multilingual support), subsidized access programs, and community-based digital literacy support (Social Media Influencers in Healthcare and Pharma: What's Their Role? | by Cyn Meyer | Medium, n.d.-b).

FUTURE RESEARCH DIRECTIONS

AI Ethics and Consumer Protection

The ethical implications of AI in healthcare is receiving much more academic and regulator attention but as yet, there is relatively little empirical evidence exploring which of these ethical design decisions best foster consumer trust and adoption behavior in real life. Questions such as: does specific transparency about algorithmic bias disclosure norms calibrate algorithmic trust for different consumer groups? (Magrabi *et al.*, 2019; Srinivasu *et al.*, 2021) What measures of informed consent for health data collection and use optimize trust and adoption while minimizing privacy concern? And how exactly can regulatory certification cues (FDA clearance, EU AI Act compliance marks) best signal trust vis A vis a brand? Are some more effective than others? (Maag *et al.*, 2025; Schacht and Lanquillon, 2025).

Personalized Consumer Engagement Models

Another limitation in that literature is the absence of longitudinal investigations of how consumer trust changes across a design experience from pre-implementation use to sustained use, experience of a failure and a return, and ultimately discontinuation. But identifying the pivotal instances in a design experience where managed trust is either cemented or shattered after a problematic recommendation, after a data security alert, after an unanticipated ROI would significantly improve the ability of designers to engineer tools for trust repair rather than trust recovery. Experience sampling methodology and platform analytics data are potential ways to explore such longitudinal studies of trust (Kerdvibulvech and Jiang, 2025; Marsden, 2025).

Future Trends in Digital Healthcare Marketing

Generative AI is quietly emerging to transform the way AI health platforms connect with consumers from providing AI-generated personalized health education content to delivering automated empathetic replies within chatbot conversations. This too prompts new questions about trust that have yet to be empirically answered: how do consumers react when they realize that the delivered 'personalized' communication was in fact generated by AI? What disclosure standards preserve trust when it comes to generative AI health communication? And as AI systems become increasingly able to infer consumers' health behaviors and emotional states, how do consumers balance the benefits of anticipatory personalization with the dread of being known? (Baracho Dittrich and Reichenbach, 2025; Umbrello and Natale, 2024).

Managerial and Marketing Implications

The body of evidence brought together in this review suggests a number of practical recommendations that will have broad appeal to the range of actors involved in defining the nature of the consumer's AI healthcare experience. For developers working on AI health platforms, the takeaway is that trust is a design requirement, not a feature. Privacy-by-design that incorporates data minimization, user control, and clear consent processes into the design from the outset, rather than treat it as a compliance add-on, is no longer just a regulatory mandate, but a key differentiator for businesses (Degen and Ntoa, 2025; Ehsan *et al.*, 2024). Explainability capability that enable users to better comprehend why the AI is suggesting a specific advice should not be optional add-on for the product but core features. The human review process and escalation pathways should also be visible to users as the visible oversight itself comprises of a trust infrastructure (Liao *et al.*, 2022; Mohamadi *et al.*, 2023).

Consistent and compelling evidence from the health care research literature indicates that by far the best channel for marketer investment regarding DTx and AIPH is one that is targeted at and co-branded with clinicians. With the physician recommendation effect size reaching 34-41% of the variance in adoption intention, a business can expect that clinician education, partnering with Continuing Medical Education providers, and investing in prescribing decision support will much more often deliver a better ROI than the same investment in DTC advertising (Stephanidis *et al.*, 2025). While influencer marketing can complement these channels, where use is appropriate, the influencer must be a credentialed physician, the commercial relationship fully transparent, and when clinical claims are made, they must be flawlessly accurate(Chan and Lee, 2023; Dobbe, 2022).

Policymakers and regulators will want to focus on drawing together a clear, harmonized regulatory landscape. Disjointed, industry-specific regulation generates uncertainty that can adversely affect both good consumers (Bengio *et al.*, 2013; Slavin, 1995) (who are less clear about product quality and safety) and conscientious innovator providers (who incur high costs in compliance and face unpredictable market conditions). Consumer-focused certification marks liken to European CE certification or FDA-related clearance designs that U.S. consumers see would significantly improve the information environment for health AI products (Patterson *et al.*, 2021; Zang *et al.*, 2025).

CONCLUSION

The narrative of AI powered healthcare and digital therapeutics, is in this respect, a story about the age-old problem of medicine trust. Patients have always had to trust their practitioners and treaters. They have always had to trust their practitioners' instructions and compliance to treatments that demand time, energy, and discomfort. What's different today is the magnitude, the rapidity, and the novelty of that relationship and the terms of trust, of that relationship. They are being asked to place trust in systems that they cannot see, interrogate, and test in the way they are used to. The literature surveyed makes clear that this trust is not out-of-reach, if those involved truly have the will to establish it. Companies that design for transparency and accountability over fiefdome; marketers who educate the consumer about the tech; healthcare providers that pitch the tools appropriately; policymakers who design a framework that balances consumer rights and corporate innovation; and academics who explore the evolution with both methodological precision and cultural astuteness. AI Healthcare market growth, is a given. In either case, the 'trust problem' will not be the deciding factor. Instead, the deciding factor will be whether this growth yields equitable, evidence based health gain, or whether it creates a field of shiny-tined, under-trusted instruments marketed, that are used, primarily, by those people who would have gotten the health gain anyway. That outcome hinges upon decisions being made today, in product design meetings, among regulators, in medical school counselling, and around the kitchen table when a clinician asks a patient what technology they would find useful. This review has attempted to chart the landscape of that decision well enough to be meaningful. The technology is there. The market is there. The only question is whether or not the trust infrastructure is there to meet it.

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ABBREVIATIONS

ADHD: Attention Deficit Hyperactivity Disorder; **AI:** Artificial Intelligence; **AIPH:** AI-Driven Personalized Healthcare; **CE:** Conformité Européenne; **CME:** Continuing Medical Education; **COPD:** Chronic Obstructive Pulmonary Disease; **DTC:** Direct-to-Consumer; **DTx:** Digital Therapeutics; **ECG:** Electrocardiogram; EU: European Union; **FDA:** Food and Drug Administration; **GDPR:** General Data Protection Regulation; **HCP:** Healthcare Professionals; **HIPAA:** Health Insurance Portability and Accountability Act; IBM: International Business Machines; **IJRT:** International Journal of Research and Technology; mHealth: Mobile Health; **ML:** Machine Learning; **OTC:** Over-the-Counter; **PEoU:** Perceived Ease of Use; PhInfluencer: Physician Influencer; **PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses; **PU:** Perceived Usefulness; **ROI:** Return on Investment; **Rx:** Prescription; SaMD: Software as a Medical Device; **SDT:** Self-Determination Theory; **TAM:** Technology Acceptance Model; **TAM+:** Extended Technology Acceptance Model; **TPB:** Theory of Planned Behavior; **TTF:** Task-Technology Fit; **UI:** User Interface; **U.S.:** United States; **USD:** United States Dollar; **UX:** User Experience; **XAI:** Explainable Artificial Intelligence.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

AUTHOR CONTRIBUTIONS

Pragati Jain, Anurag Verma and Ashish Kumar Gupta contributed to the conceptualization and writing the original draft.

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