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Rethinking Healthcare Technology Adoption: The Critical Role of Visibility & Consumption Values

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Abstract:

Engraved in the theory of consumption value (TCV), this research explores the influence of the visibility of healthcare technologies and consumption values in shaping the intentions toward the adoption of digital healthcare. The study further extends TCV by analyzing the moderating role of openness-to-change values (OTC) and gender on visibility-intention relationships. Data is gathered from consumers who are exposed to the idea of digital healthcare technology and is analyzed using structural equation modeling. Results illustrate that the visibility of digital healthcare technologies and consumption values positively influence adoption intentions. The consumption values (except social and epistemic value) mediate the visibility-intention relationship. Furthermore, OTC as a moderator is observed to be dampening the positive visibility-intention relationship, and gender as a moderator shows that that females are calculative and males are spontaneous. Theoretical implications of the study highlight the extension of TCV by uncovering the mediating-role of multidimensional consumption values and the moderating effects of openness-to-change (OTC) and gender in shaping adoption intentions toward digital healthcare technologies. Hence, visibility emerges as an extended arm to the theory, and exploring the moderating and mediating factors signifies to be useful for policymakers and practitioners in fostering better decision making.

Keywords: Adoption Intention, Healthcare Applications, Theory of Consumption Values, Values, Visibility.

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1 Introduction

Globally, the digital-health market was estimated at USD 240.9 billion in 2023 which is projected to grow with a compound annual growth rate of 21.9 percent by 2030, augmented by smartphone penetration, telehealth, and AI integration (Grand View Research, 2024). Digital tools, platforms, and services now play a central role in improving health outcomes (Matthew-Maich et al., 2016). WHO defines digital health as the usage of data and communication technologies for health (Jandoo, 2020) emphasizing its role in enhancing accessibility, efficiency, and care quality. Digital healthcare includes telemedicine, mobile health apps, electronic health records, and wearable devices (Butcher & Hussain, 2022). The rapid evolution of technology has transformed healthcare significantly (Jokisch & Schmidt, 2022). However, adoption varies across demographics and individual beliefs, requiring further exploration of its determinants (Duarte & Pinho, 2019). Research on health-related digital technologies is essential to enhance healthcare accessibility (Wu, et al., 2012), improve patient outcomes (Holden & Karsh, 2010), and optimize resource utilization (Pundziene et al., 2023). Digital tools like telemedicine, mobile health apps, and wearable devices enable remote monitoring, personalized care, and efficient data management, contributing to better health interventions (Sun et al., 2013). Moreover, these technologies empower patients with self-management tools, fostering proactive healthcare behaviors (Park et al., 2024). As healthcare systems evolve, ongoing research ensures digital innovations remain effective, secure, and inclusive (Butcher & Hussain, 2022). Research on advancing healthcare technologies is critical for understanding consumers' adoption intentions.

Recent research highlights a rising focus on understanding digital healthcare adoption at the individual level (Kessel et al., 2023), with key influencing factors such as perceived ease of use, usefulness, and social influence (Davis, 1989; Venkatesh et al., 2003; Meuter et al., 2013). While former studies have explored the evolution of wellness (Piwek et al., 2016), Service Industry innovation (Iyanna et al., 2022), and digital health awareness (Park et al., 2024), numerous critical gaps remain. Specifically, there is limited investigation done around consumption values and visibility that drives digital healthcare adoption (Ginsburg et al., 2024), scarce understanding of an individual's openness to change (Li et al., 2016), and a lack of insights into gender-specific adoption behaviors (Zhang et al., 2014). Additionally, the absence of methodological uniformity in this domain's research hinders the ability to draw broader conclusions (Piwek et al., 2016). This study addresses these gaps by examining individual-level adoption behaviors through the lens of the Theory of Consumption Values (TCV), offering both theoretical insights and practical guidance for enhancing digital healthcare adoption strategies (Duarte & Pinho, 2019). In the current study, users of healthcare technology are defined as individuals who utilize digital platforms or mobile technology to manage, monitor, or improve their health and wellness.

Our study seeks to answer these research questions:

RQ1. How does the visibility of digital healthcare tools impact their intentions to adopt?

RQ2. How do key consumption values mediate the visibility and intention relationship?

RQ3. What role does openness to change and gender play in moderating the relationship between visibility and intention?

Our study uses TCV to create that synergy between technology and wellness (Kim & Shin, 2015). By applying TCV to digital healthcare, this research seeks to uncover how different consumption values—functional, emotional, social, epistemic, and conditional—affect individuals' willingness to adopt digital healthcare solutions. Additionally, the study explores the concept of visibility, which refers to the degree to which digital healthcare tools and services are visible to potential adopters, influencing their adoption behavior (Jokisch et al., 2022). Studying digital healthcare's adoption is vital to help stakeholders, including policymakers, healthcare providers, and technology developers understand the barriers and facilitators of adoption (Piwek et al., 2016). This study highlights the concept of visibility in driving behavioral intention. Through this study, we aim to understand user perceptions, which shape adoption intentions by enhancing functional, emotional, social, epistemic, and conditional value dimensions. Key findings highlight that visibility improves technology familiarity, trust, and engagement while boosting social status and curiosity which inculcates the adoption intentions amongst users. However, it also introduces challenges like heightened privacy concerns, requiring robust data protection measures. This research underscores a dual effect: visibility promotes adoption through consumption values but necessitates careful management to mitigate privacy risks (Zafar & Sneha, 2012). Additionally, the moderating effects of openness to change, and gender roles also highlight the importance of user demographics and preferences which impact intention adoption.

This research offers valuable insights for practitioners and policymakers who want to increase the adoption of digital healthcare technologies. This study highlights how healthcare marketers must proactively educate consumers on privacy perceptions, build consumer confidence, and reduce adoption hesitation. Additionally, the study has also focused on strategies that marketing professionals should adopt for higher penetration amongst consumers conscious, and technology developers to understand consumer preferences better. This study also addresses the psychological understanding of consumers while assessing their ability to change in terms of their environment and how genders moderate the adoption intention towards this revolutionizing technology.

As healthcare systems experience challenges like rising patient demands, resource constraints, and evolving patient expectations (Talwar et al., 2020), digital technologies offer scalable solutions to enhance care quality, access, and efficiency (Butcher & Hussain, 2022). Thus, this study addresses the urgent need to improve healthcare delivery in an increasingly digital world (Guo et al., 2016). By identifying the factors that drive the successful adoption and integration of these technologies, this study will provide evidence-based insights that healthcare organizations can use to improve clinical outcomes and individuals enhance their perception by reconceptualizing the theory of consumption values and understanding the importance of visibility to rationalize the five values, driving adoption intent beyond functional utility to include broader perceived values influenced by visibility. Ultimately, these insights can inform policy decisions, guide strategies, and support the development of safer, more effective digital healthcare ecosystems. Furthermore, the study offers actionable insights for healthcare providers and developers to optimize visibility while addressing trust, privacy, and relevance, ultimately fostering sustainable user adoption.

This paper is organized as follows: In section 2 we provide an overview of TCV as the theoretical foundation for this research and a literature review on digital healthcare adoption with an emphasis on consumption values and visibility. Section 3 outlines the development of the hypotheses. Section 4 discusses the research methods used in the study. In section 5, we present the results from the statistical analyses. Section 6 discusses the findings and Section 7 concludes with the study's theoretical contributions, empirical implications, limitations, and suggestions for future research.

2 Conceptual Framework and Theoretical Framework

2.1 Theory of Consumption Values

The Theory of Consumption Values (TCV) provides a framework for understanding how consumers make decisions about purchasing and selecting specific products/services from a variety of available options (Sheth et al., 1991). In this study, we adopted TCV as our theoretical lens for three primary reasons. First, TCV is a well-established and widely recognized framework for exploring the intricacies of consumer adoption behavior (Schultz & Kumar, 2024; Swan et al., 2024) and continuance intentions (Ginsburg et al., 2024). This theory has been applied in previous research related to digital technologies and services (Schultz & Kumar, 2024; Swan et al., 2024; Talwar et al., 2020), including studies on the role of social media in enhancing brand experiences (Zollo et al., 2020). Moreover, prior literature has thrown light on the contribution of TCV towards consumer behavior in synergy with our study, such as hospitality (Tanrikulu, et al., 2021). TCV includes both cerebral and sentimental aspects of consumption and uncovers a multi-dimensional understanding of the associated values (Tanrikulu, et al., 2021). This makes it evident to visualize the adoption intentions of consumers beyond the scope of its utilitarian standards and incorporate an understanding that is related to the thought processes. This theory shows how intentions can be understood better when looked upon from multiple psychological angles that impact any person’s decision making. Hence, it is crucial to understand the positive influence of consumption values on consumers’ intentions towards healthcare technologies.

2.2 Key Constructs Used in the Study

This paper examines the interplay of variables rooted in the Theory of Consumption Value (TCV) and healthcare technology adoption. It explores how social, functional, emotional, conditional, and epistemic values influence consumer decisions alongside openness to change and visibility, which shape perceptions of utility, transparency, and the willingness to embrace digital health innovations. By integrating these dimensions, the study highlights the multifaceted nature of decision-making in healthcare technology use. These constructs are further defined in Table 1.

Table 1. Definition of Key Constructs

Variable	Definition	Reference
Theory of Consumption Value (TCV)	Based on marketing and consumer behavior, this theory explores the different dimensions of value that consumers seek and derive from products or services. It posits that consumers make purchasing decisions based on a range of values beyond just the functional attributes of a product, including emotional, conditional, social, and epistemic values.	Sheth et al., 1991
Functional Value	Refers to a product's utility and usefulness. Describes how healthcare products provide usability of smart technology to overcome illness, and diseases and maintain wellbeing	Sheth et al., 1991
Social Value	The influence of spending via social interactions where Healthcare technology gadgets serve as a fashion statement that promotes supremacy amongst social circles	Sheth et al., 1991
Emotional Value	The spending when influenced by the consumers' emotional state. In healthcare when an empathetic upliftment is provided to the consumer which in turn enables a consumer to use a specific product or technology for enabling wellbeing	Sheth et al., 1991
Epistemic Value	A curious state of mind that evokes spending to achieve novelty. For instance, a health-tech product provides a sense of care and curiosity to achieve better outcomes by leveraging technology to find healthcare solutions	Sheth et al., 1991
Conditional Value	The measure of utility based on a particular circumstance is called conditional value. Like, for every health complexity level, the approach is different. The conditions that apply before the utilization of any healthcare product/service functions as a core motive for consumer decision are unique.	Sheth et al., 1991
Openness to Change	Refers to the willingness of healthcare providers, organizations, and patients to adopt digital innovations that improve care quality and access, involving positive attitudes toward new practices perceived as beneficial and necessary to stay current with advancements	Bouckenooghe, 2010
Visibility	Refers to the extent to which digital innovations, processes, and patient data are accessible, transparent, and easy to monitor, enhancing accountability, coordination, and informed decision-making among healthcare providers and patients	Bouckenooghe, 2010

3 Hypothesis Development

Applying the theoretical framework using TCV, the study tests the relationships as illustrated in Figure 1.

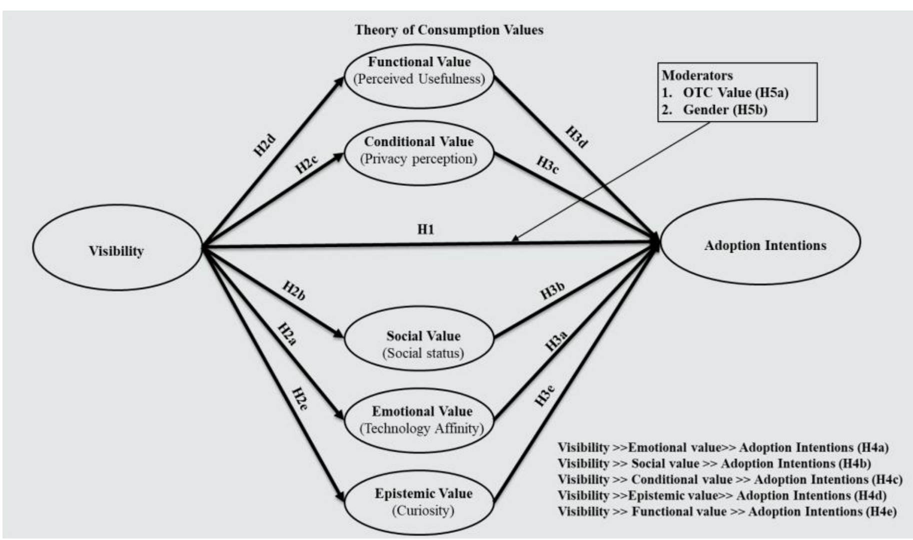

Figure 1. Hypotheses Framework

3.1 Visibility-Intention Relationship

In the context of our study, visibility refers to the extent to which the use and benefits of healthcare applications are apparent and observable within a social setting. This encompasses how readily users—such as health seekers, healthcare providers, and caregivers—can see and recognize others utilizing these technologies (Kilgus et al., 2024). Visibility becomes particularly influential when individuals observe others using the same technology, fostering recognition and reinforcing the perceived value of the technology (Zhang et al., 2014).

Past research indicates that visibility significantly impacts users' intentions to adopt technology for effective healthcare management (Jokisch et al., 2022). Studies have also explored how recurring visibility shapes consumer perceptions over time, leading to the development of positive attitudes and higher adoption intentions for a product or service (Schultz & Kumar, 2024). For example, Josiassen and Assaf, (2013) demonstrated how the visibility of social consumption influences consumers' decisions to adopt tourism destinations. Similarly, in the digital healthcare domain, a study highlighted how wearable technology, as a symbol of visible social upliftment, drives users' intentions to adopt such technologies for proactive health management (Gopinath et al., 2022).

According to Diffusion of Innovation Theory (DOI), visibility is a critical factor influencing the adoption rate of innovations (Rogers, 1995). When potential users see others benefiting from health-promoting applications, the visible advantages enhance their perceptions of the technology's usefulness and reliability, thereby increasing their intention to adopt it (Kessel et al., 2023). Likewise, Social Influence Theory underscores that observing peers or influential figures using and endorsing these technologies generates perceived social proof and normative pressure, which can strongly motivate adoption (Cialdini & Trost, 1998).

These perspectives suggest that the visibility of health-promoting applications—through demonstrable benefits and social endorsements—plays a pivotal role in motivating potential users to embrace these technologies (Park et al., 2024). By making the advantages of these technologies more apparent, visibility fosters trust, enhances perceived value, and ultimately drives adoption intentions (Kilgus et al., 2024). Thereby, we hypothesize that:

Hypothesis 1: The visibility of healthcare applications positively influences the intention to adopt them.

3.2 Visibility – Emotional Value (Technology Affinity) Relationship

In this study, we consider Technology Affinity as an emotional value and it is defined as the ability of an individual to have a preferential inclination towards the utilization of healthcare technologies as a futuristic method for acquiring holistic wellness. This inclination is primarily driven by factors such as brand attachment (Thomson et al., 2005), an empathetic value system (Bagozzi, et al., 1999), and the overall experiential feeling an individual receives (Jokisch et al., 2022; Holbrook & Hirschman, 1987). These elements contribute to making technology affinity closely aligned with a person's emotional value (Abernethy et al., 2022; Schmitt, 1999). Seminal literature suggests that there is a positive significant relationship between visibility and technology affinity in the context of digital healthcare solutions (e.g., Sze et al., 2024; Josiassen & Assaf, 2013), which indicates that increased visibility of technology features and benefits enhances users' affinity towards these technologies (Iyanna et al., 2024).

Researchers have demonstrated that visibility of the benefits and features of a technology (Rivière et al., 2024), a technology's capabilities and advantages (Venkatesh & Davis, 2000) enhance users' perceived usefulness of the technology and hence the technology affinity. Furthermore, the visibility of the features of mobile health applications as a prominent digital healthcare tool, also positively influences users' technology affinity (Rivière et al., 2024). The users who were well-informed about the specific functions and health benefits of the technologies showed a higher level of engagement and preference for using these technologies (Kilgus et al., 2024; Gao et al., 2015). Further, the visibility of health information technology features through user-friendly interfaces and clear communication significantly boost users' confidence and affinity towards using these technologies (Jokisch et al., 2022; Kim & Park, 2012). Based on the above arguments, we suggest that increased visibility of technology features and benefits positively impacts users' technology affinity, leading to greater acceptance and engagement with digital healthcare solutions. Hence, we hypothesize that:

Hypothesis 2a: Visibility of healthcare applications positively influences the technology affinity of an individual.

3.3 Visibility –Social Value (Social Status) Relationship

In this study, we conceptualize social status as a dimension of social value. This value arises from the association of digital healthcare tools with modernity, innovation, and a proactive approach to personal health management (Abernethy et al., 2022). Social status, as a fundamental aspect of an individual's presence in society, directly contributes to the broader social value system and serves as a crucial determinant of behaviors and decision-making (Venkatesh et al., 2003).

The adoption of advanced digital health solutions—such as health-promoting apps, wearables, and telehealth services—can portray individuals as tech-savvy, health-conscious, and forward-thinking in the eyes of their peers and social circles (Gopinath et al., 2022; Turner & Oakes, et al., 1986). This perceived elevation in social status motivates individuals to adopt these technologies not only for their practical health benefits but also for the recognition and esteem they garner from their association with cutting-edge innovations (Abernethy et al., 2022). This aligns with theories of social influence and identity, which suggest that behaviors and technology adoption are influenced by the desire to conform to the norms of influential social groups and enhance one's social identity (Turner & Oakes, et al., 1986). Further research supports the role of social status in shaping purchase decisions and behavioral intentions toward products and services (Abernethy et al., 2022). The visibility of healthcare technologies in social and professional contexts amplifies their perceived value in terms of social status (Gopinath et al., 2022; Truong & McColl, 2011). The adoption of visible technologies often creates a halo effect, where their utility and status become more pronounced as more people recognize their value (Amos et al., 2019).

Peer influence and visibility in professional environments also play a critical role in driving adoption (Chuah et al., 2016). Observing colleagues or influential individuals using healthcare technologies can encourage others to adopt the same technologies, thereby enhancing their perceived social status (Pundziene et al., 2023; Talukder & Quazi, et al., 2011). This dynamic is particularly potent when health-promoting apps are visibly endorsed by socially esteemed groups. Such visibility not only highlights the practical benefits but also conveys an association with prestige and social identity (Chaudhuri & Holbrook, 2001). As the adoption of health-promoting apps becomes widespread among socially influential groups, individuals are more likely to adopt these technologies to align themselves with those groups and enhance their social status (Schultz & Kumar, 2024). This visibility-driven association with desirable social identities strengthens the appeal of digital health technologies and underscores the role of social status as a critical motivator for adoption (Abernethy et al., 2022). Thus we hypothesize that:

Hypothesis 2b: Visibility of healthcare applications positively influences the social value (Social status) of an individual.

3.4 Visibility –Conditional Value (Privacy Perception) Relationship

In the context of our study, privacy perception as a part of conditional value refers to the importance that users place on the protection and confidentiality of their personal health information when considering the adoption and use of digital health technologies and applications (Angst & Agarwal, 2009). Higher privacy can influence users' perceptions of the overall value of digital healthcare solutions(Vesselkov et al., 2019), as it directly affects their trust and willingness to engage with these technologies (Bansal et al., 2010).

Studies have shown that when organizations make their privacy practices visible and easily understandable, it positively influences users' perceptions of privacy and security, increasing their trust and intention towards technology adoption (Swan et al., 2024; Guo et al., 2016). For instance, Angst and Agarwal, (2009) found that clear and transparent communication about how electronic health records (EHRs) handle patient data significantly mitigates privacy concerns, leading to higher adoption rates of EHRs. A similar study highlighted that patients frequently feel anxious about EHRs due to a dearth of transparency in data recording, accessibility, and usage. This lack of clarity can lead to reduced trust. Conversely, when patients are well-informed about how their data is being managed, their faith and readiness to participate in EHRs increase (Papadopoulos et al., 2024). This study demonstrates that when healthcare providers make their data handling practices visible and transparent, users feel more secure about their privacy, enhancing their willingness to use these digital solutions (Zafar & Sneha, 2012). Similarly, a study by Bansal et al., (2010) highlighted that transparency in privacy policies and the visibility of data protection measures positively affect users' trust in online health information systems. The research indicated that when users are well-informed about how their data is collected, used, and protected, their privacy concerns are alleviated, which in turn increases their intention to engage with these systems (Papadopoulos et al., 2024; Guo et al., 2016). Moreover, Wu, et al. (2012) in their research on mobile health applications, found that users' trust and acceptance of these technologies were significantly higher when the technologies provided clear and accessible information about privacy protections. The visibility of such information reassured users about the safety of their personal health information, thus fostering a positive relationship between visibility and perceived privacy (Kilgus et al., 2024). These studies collectively support the hypothesis that increased visibility of privacy practices positively impacts users' perceptions of privacy and security, leading to higher trust and adoption rates of digital healthcare solutions. Therefore, enhancing the visibility of privacy measures is crucial for encouraging user adoption and engagement in the context of digital healthcare. Hence, we hypothesize that:

Hypothesis 2c: Visibility of healthcare applications positively influences the conditional value (Privacy Perception) of an individual.

3.5 Visibility –Functional Value (Perceived Usefulness) Relationship

In our study, we have analyzed Functional value via Perceived usefulness (PU) of promotive healthcare applications. PU is a critical concept in the context of health promotional technologies, often derived from the theory, TAM developed by (Davis, 1989). It can be articulated as the extent to which a user believes that using a particular system or application will boost their performance and provide substantial benefits. Perceived usefulness, in the context of healthcare technologies, makes users believe that the app will help them improve their health outcomes, manage their health more effectively, or support them in achieving their health-related goals (Butcher & Hussain, et al., 2022). Visibility of these healthcare technologies provides the ability for consumers to identify the perceived usefulness and quality-associated benefits like personalization which provides an important foundation for consumer decision-making (Gopinath et al., 2022; Perrea et al., 2015). For instance, several studies (e.g., Guo et al., 2016; Park et al., 2024) highlighted the satisfaction and continuance intention towards application-assisted healthcare delivery by imparting personalization as a characteristic functional value.

Studies have also talked about perceived usefulness in terms of the utilitarian values served by aiding consumer needs, effective health delivery, and holistic health management (Rivière et al., 2024; Hung & Jen, 2012). Furthermore, various studies in the healthcare domain have highlighted the importance of visibility in identifying the effective utilitarian values of solutions like EHR (Papadopoulos et al., 2024; Alsyouf & Abdullah, 2018), m-Health apps (Gopinath et al., 2022), and E-health systems (Angst & Agarwal, 2009). Given the plausible correlation between visibility and healthcare app utility, it may be positively correlated with quality and utilitarian value, which are the cornerstones of perceived usefulness (Park et al., 2024). Therefore, we hypothesize:

Hypothesis 2d: Visibility of healthcare applications positively influences the functional values (Perceived usefulness) developed toward healthcare applications.

3.6 Visibility –Epistemic Value (Curiosity) Relationship

The perceived benefit that arises from a good or service offering novelty and stimulating curiosity is known as epistemic value (Tanrikulu, 2021; Sheth et al., 1991). In our study, curiosity refers to users' desire and motivation to explore, learn, and gain knowledge about their health and wellness through healthcare technologies. By providing personalized insights, educational content, and interactive tools, these technologies satisfy user curiosity, enhance the overall experience, and foster adherence to health recommendations (Guo et al., 2016). Research in consumer behavior highlights that proactive visibility influences decision-making at every stage (Poleacovschi & Javernick-Will, 2020). Establishing optimal visibility and promoting problem-solving abilities can stimulate the desire for novelty (Lin & Huang, 2012), creating a positive link between initial perceptions and epistemic value (Gopinath et al., 2022). For instance, studies indicate that the Information and Communications Technology (ICT) industry emphasizes "smart" healthcare solutions, such as wearables and healthcare applications, to leverage novelty and enhance visibility, thereby encouraging consumer interest (Chuah et al., 2016). Factors such as brand visibility, advertisements, communication, app design, functionality, and connectivity contribute significantly to user curiosity (Guo et al., 2016). "Smart applications" that offer personalized health information for self-diagnosis (Piwek et al., 2016) exemplify proactive healthcare by blending visibility and epistemic value, leading to greater user engagement and adoption. Similarly, healthcare technologies providing real-time analytics and insights enhance users' understanding of their health, support preventive care, and foster curiosity (Butcher & Hussain et al., 2022). As users explore and learn through these technologies, their positive attitudes toward the technology strengthen, along with an improved sense of control over their health (Gopinath et al., 2022). This epistemic value, derived from sustained visibility and the satisfaction of curiosity, enhances the user experience by fulfilling intrinsic motivations (Kilgus et al., 2024). It also positively influences attitudes, perceived control, and behavioral intentions toward adopting healthcare technology (Schultz & Kumar, 2024). Since the past research has found a positive relationship between visibility and epistemic value, we similarly hypothesize:

Hypothesis 2e: Visibility of healthcare applications positively influences the epistemic values developed toward healthcare applications.

3.7 Consumption Values – Intentions Relationship

The literature highlights the significance of consumption values in understanding the intention towards adopting healthcare-promotive technologies (Schultz & Kumar, 2024; Pai & Huang, et al. 2011). Pivotal literature also suggests that consumers' consumption values impact individual-level retort toward proactive health management (Swan et al., 2024; Piwek et al., 2016) because values direct decision making (Chuah et al., 2016) and consumers proactively start taking care of themselves if the changes are aligned to their consumption values like perceived usefulness (Talwar et al., 2020), social influence (Guo et al., 2016) and seek novel solutions. In terms of consumer beliefs concerning healthcare technologies, the literature suggests five consumption values that impact health and wellness-related decisions, and magnify the intention to adopt health-tech solutions as an integral part of their healthcare journey (Pai & Huang, et al. 2011).

3.7.1 Emotional Value (Technology Affinity) – Intention Relationship

Consumers see a product's value as increasing with the amount of confidence they get from it (Iyanna et al., 2022). Studies in the past have determined the sense of emotional attachment to "empathetic brands" is a powerful part of the uniqueness that can be attained through technological affinity toward health and wellness (Choi & Kim, 2016). A health app frequently makes use of cutting-edge app technology with the resources and assistance of overall wellness to guarantee that its features are both amusing and useful continuously meeting the emotional wants of users (Ginsburg et al., 2024). Research has demonstrated that individuals with a high affinity for technology are more likely to perceive technological solutions as useful, which significantly boosts their intention to adopt these technologies (Kasilingam, 2020). For example, studies have found that users with a greater affinity for technology showed a higher inclination toward using it, leading to a stronger intention to use the technology (Iyanna et al., 2022; Venkatesh et al., 2003). This indicates that technology affinity directly enhances the intention to use digital healthcare solutions by positively influencing these critical perceptions (Jokisch et al., 2022). Additionally, a study observed that users who exhibit a strong preference and comfort for technology are more inclined toward the use of health-related technologies. They found that technology affinity significantly correlated with users' intention to use electronic health record systems, highlighting the importance of positive technology attitudes and intentions in driving adoption (Pundziene et al., 2023; Kuo et al., 2013). Furthermore, Kim and Garrison (2009) showed that technology affinity positively impacts users' behavioral intentions towards e-health applications. Their research indicated that individuals with high technology affinity are more inclined to adopt and consistently use e-health solutions, as they feel more confident and competent in navigating these platforms (Kim & Garrison, 2009). This reinforces the notion that technology affinity is a crucial determinant of users' intention to engage with digital healthcare technologies (Pundziene et al., 2023). These studies collectively support the hypothesis that a high level of technology affinity positively impacts users' intention to adopt digital healthcare solutions (Abernethy et al., 2022). Therefore, efforts to enhance users' comfort and positive attitudes toward technology can significantly increase their adoption intentions in the context of digital healthcare. Hence, we hypothesize that:

Hypothesis 3a: Technology Affinity (Emotional Value) of healthcare applications positively impacts the intention to adopt healthcare applications for overall well-being.

3.7.2 Social Value (Social status) – Intention Relationship

Consumers interested in acquiring social worth are more likely to use products and services to achieve their desired social standing (Dinh & Lee, 2024). Our study highlights this value of desirability through social status value. In the context of health-promoting technologies, users might be more interested in product features that improve their sense of status, social acceptance, and symbolic significance to others than in the actual functionality and performance of the product (Petrescu et al., 2024; Turel et al., 2010). Since experience purchases let customers emphasize themselves above the acquired item, researchers have talked about the importance of these purchases in gaining social worth (Abernethy et al., 2022). For instance, Meuter et al., (2013) highlighted the scope to which the technology offers a feeling of individuality, freedom, and being in control. An individual's interactions with others can also impact the decision to accept or reject a technology (Talwar et al., 2020). For instance, social value was found to be positively connected with continued intentions for online wellness services and mobile health apps, respectively (Chuah et al., 2016). Social Cognitive Theory (SCT) adds that individuals learn and emulate behavioral intentions observed in their social groups (Bandura, 1986). Thus, those with higher social value are more likely to encounter and adopt health-promoting behaviors modelled by peers, further reinforcing their intention to use health applications (Petrescu et al., 2024). These theories collectively suggest that individuals with greater social value are more likely to recognize the benefits and feel the social support needed to engage with health-promoting technologies, thereby strengthening their adoption intention (Ajzen, 2012; Bandura, 1986). Thereby we hypothesize:

Hypothesis 3b: Social status (Social Value) of healthcare applications positively impacts the intention to adopt healthcare applications for overall wellbeing.

3.7.3 Conditional Value (Privacy Perception) – Intention Relationship

Studies have shown that safety drives the sustained use of healthcare technologies (Silvera-Tawil, 2024). For instance, Chen and Chan, (2011) reported a positive influence of transparency of information transfer, on utilization intention in the context of patient wellbeing. Similar studies (Abernethy et al., 2022; Kim & Park, 2012) suggest that consumers frequently use wearables, home healthcare devices, applications, and other healthcare items in response to circumstances that support a demand for a preferential or conditional value, which makes them feel secure and safe. Also, Bansal et al., (2010) discovered that conditional value (e.g., privacy and transparency) affects individuals' choice behavior in the context of health technology. Beyond healthcare, other service industries have found a similar positive association. For instance, research on tourism and hospitality has highlighted the significance of conditional value and regarded it as a crucial consumption value for travelers (Hur et al., 2017). When users perceive an app as safe and convenient, their PU and ease of use increase, thereby positively driving their technology's adoption intention (Butcher & Hussain, 2022; Davis, 1989). If a health-promoting app is perceived to offer a significant advantage over existing solutions, such as being safe (Agarwal & Prasad, 1997), the rate of adoption will likely increase. This perceived advantage enhances the app's appeal and encourages quicker uptake among potential users (Gopinath et al., 2022).

Thus, a positive association between conditional value and intentions can be inferred:

Hypothesis 3c: Privacy Perception (Conditional Value) of healthcare applications positively impacts the intention to adopt healthcare applications for overall wellbeing.

3.7.4 Functional Value (Perceived Usefulness) – Intention Relationship

The relationship between functional value, particularly perceived usefulness, and intention to use digital healthcare solutions is well-documented (Abernethy et al., 2022; Butcher & Hussain, 2022; Jokisch et al., 2022; Chuah et al., 2016). Perceived usefulness, as highlighted in TAM by Davis (1989), is a key driver of users' intentions to adopt technology, including digital healthcare solutions, where perceived benefits in health management significantly influence adoption. Similarly, Venkatesh et al., (2003) extended the TAM with the Unified Theory of Acceptance and Use of Technology (UTAUT), emphasizing perceived usefulness (performance expectancy) as a crucial predictor of technology adoption intentions. Their findings were extended and show that users' belief in the utility and advantages of digital healthcare solutions significantly enhances their intention to use these technologies (Iyanna et al., 2022). Moreover, Holden and Karsh (2010) explored healthcare professionals' use of health information systems and found that perceived usefulness strongly predicts their intention to adopt these systems. Their study concluded that healthcare providers are more prone to using digital health solutions if they trust that these tools will improve their job performance or patient outcomes. Chau and Hu, (2002) investigated the adoption of telemedicine technology and determined that perceived usefulness significantly influenced physicians' intentions to adopt telemedicine solutions. These observations further underscore the importance of functional value in the healthcare sector, where the perceived effectiveness and benefits of technology directly affect adoption intentions (Pundziene et al., 2023; Chau & Hu, 2002). Therefore, the relationship between perceived usefulness and the intention to use digital healthcare solutions is well-established. Users who perceive these solutions as beneficial and valuable in enhancing their health management are significantly more likely to intend to adopt them. Thus, we hypothesize:

Hypothesis 3d: Perceived Usefulness (Functional Value) of healthcare applications positively impacts the intention to adopt health-tech solutions for overall wellbeing.

3.7.5 Epistemic Value (Curiosity) – Intention Relationship

Curiosity often acts as a strong motivator for individuals to adopt innovative solutions, including digital healthcare technologies. Literature suggests that curiosity and the desire for knowledge significantly drive the adoption of new technologies. For instance, Dhir et al. (2021) identified "reasoning for" as a motivator that can positively influence managers' perceptions toward intended behavior, highlighting the importance of cognitive engagement in decision-making (Dhir et al., 2021). Individuals who seek to understand digital healthcare and explore these technologies are more likely to perceive them positively and intend to use them. Further, studies have shown that the pursuit of knowledge and the satisfaction derived from learning about new technologies can bridge the attitude-intention gap. Studies also found that context-specific reasoning, which includes epistemic motivations, can significantly influence individuals' choices and behaviors (Petrescu et al., 2024; Lin et al., 2012; Myyry et al., 2009). This suggests that those who find epistemic value in digital healthcare solutions are more likely to develop a strong intention to adopt these technologies. Moreover, research by Claudy et al. (2013) supports the notion that context-specific reasoning, driven by a desire for knowledge, can narrow the gap between attitudes and intentions. This study indicates that individuals who are intellectually engaged and curious about digital healthcare solutions are more likely to move from positive attitudes to concrete intentions to adopt these solutions (Claudy et al., 2013). Another study emphasizes that understanding the decision-making process is crucial in technology adoption (Abma et al., 2020). Their findings suggest that epistemic value, as a form of intrinsic motivation, plays a significant role in shaping individuals' intentions to engage with new technologies (Abma et al., 2020). Therefore, the relationship between epistemic value and the intention to use digital healthcare solutions is well-established. Individuals driven by curiosity and the desire for knowledge are significantly more likely to intend to adopt and use digital healthcare technologies. Thus, we hypothesize that:

Hypothesis 3e: Curiosity (Epistemic Value) of healthcare applications positively impacts the intention to adopt health-tech solutions for overall wellbeing.

3.8 Mediating Role of Consumption Values

3.8.1 Mediating Role of Technology Affinity on Visibility – Intention Relationship

Research has shown that when the features and benefits of a technology are made visible and easily understandable, they positively influence users' attitudes toward the technology, enhancing their technology affinity (Chuah et al., 2016). For example, Venkatesh and Davis (2000) demonstrated that clear visibility of a technology's capabilities and advantages enhances users' perceived ease of use, leading to greater technology affinity. This increased affinity for technology then positively impacts users' intention to adopt these technologies. Furthermore, studies have found that technology affinity itself is a strong predictor of users' intention to adopt digital healthcare solutions. For instance, Kuo et al. (2013) observed that users with a strong preference and comfort for technology, intend to use health-related technologies proactively. A significant link between technology affinity and the intention to use electronic health record systems was found by Iyanna et, al. (2022), indicating that technology affinity is a crucial mediator in the association between visibility and adoption intention. Additionally, Kim and Garrison (2009). found that individuals with high technology affinity are more inclined to adopt and consistently use e-health solutions, reinforcing the significance of technology affinity as a mediator between visibility and intention. By increasing the visibility of digital healthcare solutions, users develop a higher affinity for the technology that significantly enhances their adoption intentions towards these solutions (Gopinath et al., 2022). This mediated relationship suggests that efforts to improve the visibility of digital healthcare technologies can effectively boost user adoption by fostering greater technology affinity. Thus:

Hypothesis 4a: Technology Affinity (Emotional Value) partially mediates the positive relationship between visibility and intention to adopt healthcare applications.

3.8.2 Mediating Role of Social Status on Visibility – Intention Relationship

Research has shown that while visibility can enhance the ease of use of technology and its usefulness, it does not necessarily influence users' intention to adopt the technology if the adoption is mediated by social status concerns (Dinh & Lee, 2024; Meuter et al., 2013). For instance, Venkatesh and Davis (2000) found that while visibility improved users' perceptions of technology, these perceptions did not always translate into adoption intentions when users were primarily motivated by social status considerations. Thus social status might not effectively mediate the relationship between visibility and intention (Sze et al., 2024). Additionally, Kim and Shin (2015) found that while the visibility of mobile health applications' features could enhance user engagement, it did not significantly affect the intention to use these technologies when users' primary concern was their social standing. The researchers noted that users often adopt technologies to align with social norms or to gain social approval, which are motivations not necessarily driven by visibility alone. Thus, the relationship between visibility and intention to adopt digital healthcare solutions is not fully mediated by social status. This suggests that while making features and benefits visible is important, it does not directly translate to higher adoption intentions if users are primarily motivated by social status considerations (Talwar et al., 2020).

Hypothesis 4b: Social Status (Social Value) partly mediates the positive relationship between visibility and intention to adopt healthcare applications.

3.8.3 The Mediating Role of Privacy Perception on Visibility – Intention Relationship

Research has shown that when the privacy practices of digital healthcare solutions are made visible and understandable it enhances users' perceptions of privacy, which in turn increases their intention to adopt these technologies. For example, research has shown that clear and transparent communication about how electronic health records (EHRs) handle patient data significantly mitigates privacy concerns, leading to higher adoption rates of EHRs (Angst & Agarwal, 2009). This indicates that visibility of privacy practices enhances perceived privacy, which positively influences users' adoption intentions. Furthermore, studies have indicated that privacy concerns are a critical factor in users' decision to adopt digital healthcare solutions. For instance, Kilgus et al. (20204) found that transparency in privacy policies and the visibility of data protection measures positively affect users' trust in online health information systems. Thus transparency reduces privacy concerns and increases users’ intention to use these systems suggesting that making privacy practices visible is crucial for addressing privacy concerns and fostering adoption intentions (Bansal et al., 2010). Additionally, Kim and Park (2012) highlighted that the visibility of privacy features in mobile health applications significantly boosts users' confidence and intention to use these technologies. Their research showed that when users are well-informed about how their data is protected, their privacy concerns are alleviated, which in turn enhances their intention to adopt these technologies. The results of these studies reinforce how privacy acts as a mediator in the relationship between visibility and intention. Thus, by increasing the visibility of privacy practices, users' perceptions of privacy are enhanced, which significantly boosts their intention to adopt digital healthcare solutions. Collectively, these findings support the hypothesis that privacy mediates the positive relationship between visibility and intention to use digital healthcare solutions.

Hypothesis 4c: Perceived Privacy positively mediates the positive relationship between visibility and intention to adopt healthcare applications.

3.8.4 The Mediating Role of Perceived Usefulness on Visibility – Intention Relationship

Visibility, or the degree to which the use of digital healthcare solutions is observable by others, can enhance individuals' perceptions of the usefulness and benefits of these solutions and significantly impact their intention to adopt such technologies (Chuah et al., 2016). Research indicates that visibility can enhance perceived usefulness, a core component of functional value. Aschemann-Witzel and Aagaard (2014) suggest that reasons and attitudes towards specific behaviors are crucial in understanding decision-making processes. When digital healthcare solutions are highly visible, users are more likely to recognize and appreciate their benefits, which strengthens the perceived usefulness of these technologies. In terms of digital healthcare solutions, visibility influences perceived usefulness (functional value), which in turn impacts the intention to adopt these technologies (Bansal et al., 2010). Rydell and McConnell (2006) argue that decision-making rules vary with scenario complexity, emphasizing the importance of mediators in understanding behavioral intentions. Thus, visibility makes the functional benefits of digital healthcare solutions more apparent, which simplifies the decision-making process and enhances the intention to use these solutions (Rydell & McConnell, 2006). Therefore, the positive relationship between visibility and the intention to adopt digital healthcare solutions, mediated by functional value, is well-supported. High visibility enhances perceived usefulness which significantly boosts the intention to use digital healthcare technologies.

Hypothesis 4d: Perceived Usefulness positively mediates the positive relationship between visibility and intention to adopt healthcare applications.

3.8.5 Mediating Role of Curiosity on Visibility – Intention Relationship

Studies suggest that investigating the mediation of factors can help decipher the mechanisms motivating decision-making. In the context of digital healthcare, visibility can stimulate users' curiosity and their desire to learn more about these solutions, thereby increasing the epistemic value they perceive (Aschemann-Witzel & Aagaard, 2014). Moreover, Ajzen et al. (2015) highlight that reasoning processes, influenced by visible cues, can directly and indirectly shape attitudes and intentions. When users see others benefiting from digital healthcare solutions, their curiosity and desire to understand these technologies grow, which enhances the epistemic value and strengthens their intention to adopt these solutions (Ajzen, 2012). The role of epistemic value as a mediator is further supported by Bansal et al. (2010), who found that reasoning mediated the relationship between values and attitudes. In terms of digital healthcare, this suggests that visibility influences curiosity and knowledge pursuit (epistemic value), which in turn impacts the intention to adopt these technologies (Bansal et al., 2010). Rydell and McConnell (2006) argue that decision-making rules vary with scenario complexity, emphasizing the importance of mediators in understanding behavioral intentions. Visibility makes the knowledge benefits of digital healthcare solutions more apparent, which simplifies the decision-making process and enhances the intention to use these solutions (Rydell & McConnell, 2006). Therefore, the positive relationship between visibility and the intention to adopt digital healthcare solutions, mediated by epistemic value, is well-supported. High visibility enhances curiosity and the pursuit of knowledge, which in turn significantly boosts the intention to use digital healthcare technologies.

Hypothesis 4e: Curiosity positively mediates the positive relationship between visibility and intention to adopt healthcare applications.

3.9 The Moderating Role of Openness to Change on Visibility – Intention Relationship

Research indicates that while visibility generally enhances users' intention to adopt technologies by making their benefits more apparent, this effect can be moderated by individual differences in openness to change (Yadav et al., 2022). Individuals with high openness to change might already be inclined to adopt new technologies making the visibility of features less impactful on their intention. For example, studies found that visibility significantly influences technology adoption, but its impact varies based on individual characteristics including openness to new experiences (Venkatesh & Bala, 2008). This suggests that those who are naturally open to change might not need as much visibility to be persuaded to adopt new technologies. Kim and Malhotra (2005) support this dampening effect by showing that individuals who are inherently more open to new experiences and changes in technology tend to have higher baseline intentions to adopt new technologies regardless of how visible or well-communicated the benefits are. For these individuals, the additional visibility does not significantly increase their intention to adopt because their openness to change already drives their behavioral intention (Chakraborty et al., 2021). Additionally, Rogers’s (1995) study on the diffusion of innovations highlights that early adopters, who typically exhibit high openness to change, are less influenced by marketing and visibility efforts compared to late adopters. These early adopters are more motivated by intrinsic curiosity and a desire for novelty, thus the moderating effect of openness to change dampens the impact of visibility on their intention to adopt digital healthcare solutions (Rogers, 1995). Therefore, while visibility generally promotes the intention to adopt digital healthcare solutions, the positive effect of visibility is dampened among those with high openness to change.

Hypothesis 5a: Openness to change dampens the positive relationship between visibility and intention to adopt healthcare applications.

3.10 The Moderating Role of Gender on Visibility- – Intention Relationship

The role of gender in technology adoption has been extensively explored. For example, Hoque (2016) found men and women in Bangladesh behave differently in the adoption of health technology. Other research suggests that women are more likely to be influenced by visible cues than men in their decision-making processes. For instance, Venkatesh et al. (2003) found that women are particularly responsive to social influence and visibility in technology adoption contexts. This implies that when digital healthcare solutions are prominently visible, women are more inclined to perceive these technologies positively and develop stronger intentions to adopt them. Females often rate visibility and social influence factors higher than males during adoption decisions, emphasizing the moderating role of gender in this relationship (Gefen & Straub, 1997). Others (Scherer et al., 2019) found that women are more influenced by external factors, such as visibility and social norms, when considering digital healthcare solutions. This underscores the stronger impact of visibility on adoption intentions among females compared to males. Additionally, empirical evidence supports the notion that females exhibit higher engagement levels with visible health technologies. Duarte and Pinho (2019) observed that women are more likely to adopt and engage with health technologies that are visibly endorsed by peers or healthcare providers. This finding further validates the hypothesis that visibility has a positive effect on adoption intentions, particularly among women.

Hypothesis 5b: Females have a positive moderating influence on the relationship between visibility and intention to adopt healthcare applications as compared to males.

4 Method

4.1 Study Variables

Our survey used pre-validated scales to measure the constructs. To guarantee the robustness of these measures, the questionnaire was reviewed by three academic experts in healthcare, technology, and psychology, as well as three senior managers from the digital healthcare industry. Their feedback led to minor adjustments for enhanced face validity. Subsequently, we conducted a pilot study with 30 healthcare technology users who were invited to complete the questionnaire and participate in interviews to confirm the clarity of each item. Upon receiving their feedback, some survey items were revised for better clarity and association. The final questionnaire, consisting of 9 variables and 41 items, was then utilized for data collection (see Table 2). The measures demonstrated the desired levels of validity and reliability.

Table 2. Measures Used for Data Collection

Measure	Items	Reference	α#	CR	Scale
Intention (Int)	"I predict I will use health-promoting applications in the future." "I plan to use the health-promoting applications in the future." "I expect my use of these health apps, to continue in the future."	Venkatesh et al., 2003	0.993	0.813	7-point LS
Technology Affinity (TA)	"I am confident that, I can learn technology-related skills." "I have difficulty understanding most technological matters." "I feel apprehensive about using technology." "When given the opportunity to use technology, I fear I might damage it in some way." "I am sure of my ability to interpret technological output." "Technological terminology sounds like confusing jargon to me." "I have avoided technology because it is unfamiliar to me." "I am able to keep up with important technological advances." "I hesitate to use technology for fear of making mistakes I cannot correct."	Meuter et al., 2003	0.858	0.763	7-point LS
Perceived Usefulness (PU)	"Using Health promotion apps will address my health management needs" "Using Health promotion apps will enhance the effectiveness of my health management" "Overall, using Health promotion apps will be useful in managing my health."	Taylor & Todd, 1995	0.880	0.745	7-point LS

Curiosity (CU)	"I use health-promoting apps because I wanted to know what their services are like." "My friend who uses health-promoting apps made me curious to use it for myself" "I use health-promoting apps because I wanted to learn new ways of living- like using smartphones and wearable technologies for integrated healthcare delivery" "I use health-promoting apps because I wanted to know what their services are like"	Pura, 2005	0.850	0.831	7-point LS
Social Status (SS)	"Using health-promoting apps helps me gain social approval" "Using health-promoting apps changes the way I am perceived by others" "Using health-promoting apps helps me stand out among my peers" "Using health-promoting apps gives me a chance to show off my proactive health management experiences to others" "I have higher social status when being healthy, using these health-promoting apps" "After using health-promoting apps, I feel like a smarter person"	Choe & Kim, 2019; Tandon et al., 2021; Talwar et al., 2020	0.900	0.839	7-point LS
Privacy perception (PP)	"My use of health-promoting apps would cause me to lose control over the privacy of my information" "Signing up for and using health-promoting apps would lead to a loss of privacy for me because my personal information could be used without my knowledge." "[Others] might take control of my information if I used health-promoting apps"	Featherman et al., 2003	0.896	0.799	7-point LS
Value: Openness to Change (V-OTC)	"Thinking up new ideas and being creative is important to him/her. He/she likes to do things in her own original way." "It is important to him/her to make his/her own decisions about what he/she does. He/she likes to be free and not depend on others." "He/she likes surprises and is always looking for new things to do. He/she thinks it is important to do lots of different things in life"	Schwartz, 2012	0.892	0.871	7-point LS
Visibility (Vis)	"I have seen advertisements about health-promoting apps." "It is common to find people who use health-promoting apps." "I have seen others availing the benefits of health-promoting apps." "All my friends/family are using health-promoting apps."	Johnson et al., 2018	0.899	0.766	7-point LS

Note: α#, Cronbach's alpha values; CR, composite reliability; 7-point Likert scale (7-point LS), scale from 1 (not Important) to 7 (of supreme importance)

4.2 Data Collection

Data was collected from the users of healthcare technology across more than 50 cities in India using a survey instrument. In this study, users of healthcare technology are defined as individuals who utilize digital platforms or mobile technology to manage, monitor, or improve their health and wellness. While utilizing these technologies, the users were involved in a proactive health monitoring and wellness perspective not just for themselves but also for their families over a long period. A total of 800 questionnaires were distributed online and 382 responses were received. After filtering out 21 incomplete responses (with more than 10 percent of the questions unanswered) and 43 unengaged responses, 318 valid responses were finalized for the analysis. To determine the sample size, we applied the rule of ten times the number of items (Hair Jr et al., 2014). Using a snowball sampling technique facilitated access to a dispersed population across diverse regions of India but may have introduced potential biases, such as the over-representation of certain networks or groups that are more active in using healthcare applications. Despite efforts to reach a diverse sample, the reliance on participants to recruit others within their networks may limit the generalizability of the findings. Participants were informed about the research objectives and the academic purpose of the inquiry before their participation. Their participation was voluntary, without any offered incentives, and they were free to withdraw at any point during the process.

4.3 Data Analysis

We employed SPSS 25 for statistical analysis, and AMOS 26 for structural equation modeling (SEM) to analyze our data (318 people). The appropriateness of the sample size for exploratory factor analysis (EFA) was confirmed with a KMO value of 0.704 and Bartlett's Test ($\chi^2 = 9163.956$; df = 561; $p < 0.000$) (Habibi et al., 2020). EFA identified 8 distinct clusters with factor loadings exceeding 0.615 (Table 3), ensuring convergent validity. The factor correlation matrix showed no significant cross-loadings, confirming discriminant validity. Following a two-step approach, confirmatory factor analysis (CFA) validated construct reliability and fit the measurement model. SEM was then conducted to evaluate the model's fit and the strength of hypothesized paths, with reference thresholds detailed in Figure 2. Mediation effects were assessed using 2000 bootstrap samples, as recommended by Dhir et al., (2021). We addressed potential common method bias (CMB) using measures outlined by (Podsakoff et al., 2012), including collecting data from healthcare application users across various Indian regions. Harman's single-factor test indicated that the largest factor accounted for only 23.6 percent of the variance, below the 50 percent threshold, suggesting CMB was not a concern. Additionally, the common link factor approach was applied, and adjustments were made to account for observed CMB in factor score calculations. Multicollinearity was assessed by calculating variance inflation factors (VIFs), which were all below the threshold of 3 (O'Brien, 2007), confirming no multicollinearity issues. These steps ensured the robustness and validity of our analytical approach.

PARAMETERS	THRESHOLD VALUE
Composite reliability	CR ≥0.6 (Bagozzi & Yi, 1988)
Average variance extracted	AVE ≥0.5 (Fornell & Larcker, 1981)
$\chi2$/df	($\chi2$/df ≤3) (Hu & Bentler, 1999)
RMSEA	(RMSEA ≤0.10)
CFI	(CFI ≥0.9)

Figure 2. Threshold Used for Analysis (Bagozzi & Yi, 1998; Fornell & Larker, 1981; Hu & Bentler, 1999)

Table 3. EFA of the variables

	SV_SS	**INT**	**VIS**	**V_OTC**	**EV_TA**	**CV_PP**	**EP_CU**	**FV_PU**
SV_SS1	0.947							
SV_SS3	0.663							
SV_SS2	0.629							
INT2		0.864						
INT1		0.737						
INT3		0.513						
VIS3			0.734					
VIS2			0.713					
VIS1			0.641					
V_OTC3				0.933				
V_OTC4				0.81				
EV_TA2					0.716			
EV_TA4					0.698			
EV_TA3					0.683			

CV_PP1						0.911		
CV_PP2						0.756		
EPV_CU1							0.783	
EPV_CU2							0.733	
FV_PU1								0.926
FV_PU2								0.498

Abbreviations: INT- Intention towards adoption of healthcare applications; EV_TA- Emotional Value (Technology Affinity) towards healthcare applications adoption; FV_PU- Functional Value (Perceived Usefulness); SV_SS- Social Value (Social Status) developing towards healthcare applications adoption; CV_PP- Conditional value (Privacy Perception) towards healthcare applications adoption; EpV_CU- Epistemic Value (Curiosity) V_OTC- Openness to change as a value towards adoption of healthcare applications; Vis-Visibility.

5 Results

5.1 Participants' Profile

Table 4 shows the participants' profiles in terms of their educational background, age, and gender. Data suggests that most of the respondents were well-educated.

Table 4. Demographic Profile of Participants

Demographic Factor	Demography	Total	% F	%M
Average age	21-30	228	49%	51%
	31-40	42	5%	95%
	41-50	54	24%	76%
	51-60	32	34%	66%
	60+	29	62%	38%
Educational Qualification	High School	10	40%	60%
	Graduate	128	52%	48%
	Post Graduate	226	48%	52%
	PhD	11	18%	82%
	Post Doctorate	10	30%	70%

5.2 Measurement Model

With model fit measures ($\chi 2/df = 2.52$, CFI = 0.984, SRMR = 0.027, RMSEA = 0.069, PClose = 0.020), we established the measurement model's desired validity and reliability (Kline, 2015). The desired values of composite reliability (CR >0.7) and average variance extracted (AVE >0.5) were also observed (Table 5).

Table 5. Validity and Reliability of Study Variables

Variables	CR	AVE	SV_SS	INT	VIS	V_OTC	EV_TA	CV_PP	EPV_CU	FV_PU
SV_SS	0.839	0.636	**0.797**							
INT	0.813	0.602	0.265***	**0.776**						
VIS	0.766	0.535	0.477***	0.376***	**0.731**					
V_OTC	0.871	0.772	0.118†	-0.04	-0.131*	**0.879**				
EV_TA	0.763	0.601	-0.067	-0.219**	-0.335***	0.161**	**0.775**			
CV_PP	0.799	0.666	-0.163*	0.161	0.186*	0.524	0.091	**0.82**		

EPV_CU	0.831	0.711	0.350***	0.588***	0.423***	0.130*	0.133*	0.229**	**0.843**	
FV_PU	0.745	0.594	0.41	0.638	0.14	0.382	0.018	0.198	0.416	**0.771**
Abbreviations: SV_SS, social value (social status); EV_TA, emotional value (technology affinity); CV_PP, conditional value (privacy perception); EPV_CU, epistemic value (curiosity); FV_PU, functional value (perceived usefulness)										

5.3 Structure Model

SEM resulted in desired model fit (χ2/df = 1.221, CFI = 0.998, SRMR = 0.017, RMSEA = 0.026, PClose = 0.939). The model explains 58 percent variance in functional values driving the intentions, 7 percent in conditional value, 53 percent in social value, and 37 percent in emotional value (Figure 3). Table 6 illustrates the hypotheses that are supported and those not supported.

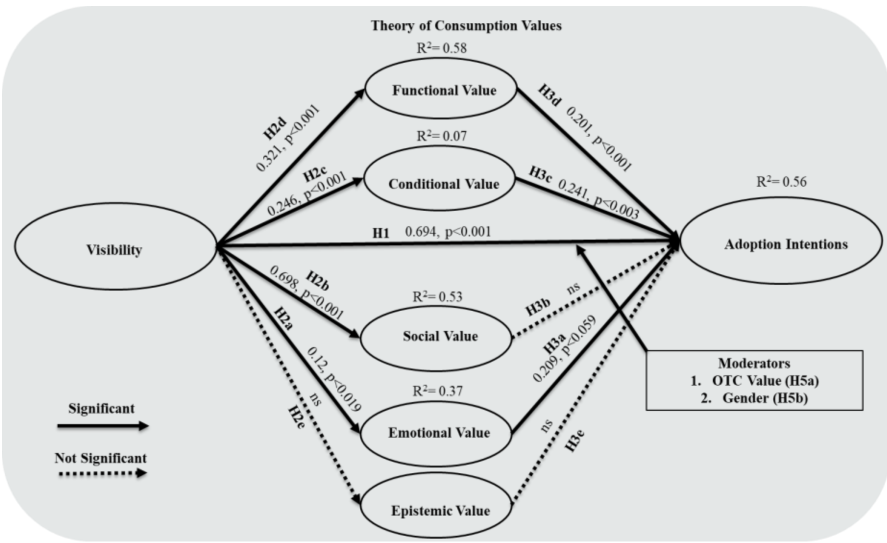

Figure 3. Threshold Used for Analysis (Bagozzi & Yi, 1998; Fornell & Larker, 1981; Hu & Bentler, 1999)

Table 6. Hypothesis Testing Results

Hypothesis	**Path**	**Beta**	**P value**	**Hypothesis supported (yes/no) at 90% CI**
H1	Visibility > intention	0.694	**	Yes
H2a	Visibility > EV_TA	0.12	0.019	Yes
H2b	Visibility > SV_SSV	0.698	**	Yes
H2c	Visibility > CV_PP	0.246	**	Yes
H2d	Visibility > FV_PU	0.321	**	Yes
H2e	Visibility > EPV_CU	NS		No
H3a	EV_TA > Intentions	0.209	0.059	Yes
H3b	SV_SSV > Intentions	NS		No
H3c	CV_PP > Intentions	0.241	0.003	Yes
H3d	FV_PU > Intentions	0.201	**	Yes
H3e	EPV_CU > Intentions	NS		Yes
Abbreviations: SV_SS, social value (social status); EV_TA, emotional value (technology affinity); CV_PP, conditional value (privacy perception); EPV_CU, epistemic value (curiosity); FV_PU, functional value (perceived usefulness); *p < 0.050; **p < 0.010; ***p < 0.001; NS, Non-significant				

5.4 Mediation Analysis

The mediation analysis examined the mediation role of the Functional value (Perceived usefulness), Emotional value (Technology Affinity), Social value (Social status), Conditional value (privacy perception), and Epistemic value (curiosity) in the relationship between visibility and intention to adopt healthcare technologies. Table 7 reports the results that illustrate Functional value, Technology affinity, and Privacy perception fully mediating the visibility intention relationship of healthcare technologies, while social status and curiosity remain a non-significant mediator. All these mediating effects were observed at a 90 percent confidence interval.

Table 7. Indirect Effects

Hypothesis	Indirect Path	Beta Value	P-Value	Hypothesis supported (Yes/No) at 90% CI
H3a	VIS>> EV_TA>>INT	0.025	0.055	Yes
H4b	VIS>> SV_SS>>INT	**NS**	**NS**	No
H4c	VIS>> CV_PP>>INT	0.059	0.009	Yes
H4d	VIS>> FV_PU>>INT	0.18	0.01	Yes
H4e	VIS>> EPV_CU>>INT	**NS**	**NS**	No
Abbreviations: SV_SS, social value (social status); INT, intention; VIS, visibility; EV_TA, emotional value (technology affinity); CV_PP, conditional value (privacy perception); EPV_CU, epistemic value (curiosity); FV_PU, functional value (perceived usefulness); *p < 0.050; **p < 0.010; ***p < 0.001; NS, Non-significant.				

5.5 Moderation Analysis

The moderation of openness to change and gender on the association between visibility, users' values, and intention toward healthcare technology's adoption was analyzed, and the results are shown in Figure 4. The study suggests that the users' openness to change (a) dampens the positive relationship between visibility and intention to adopt healthcare technologies. Figure 5 shows that the gender of an individual also dampens the positive relationship between visibility and intention to adopt healthcare technologies. The moderating influence of users' openness to change and gender was observed only in the case of the direct relationship between visibility and intention to adopt. However, social status and intention to adopt healthcare technologies had a moderating effect from openness to change alone, which is also at a 90 percent confidence interval. We did not observe any significant moderating influence of technology affinity and privacy perception on other relationships.

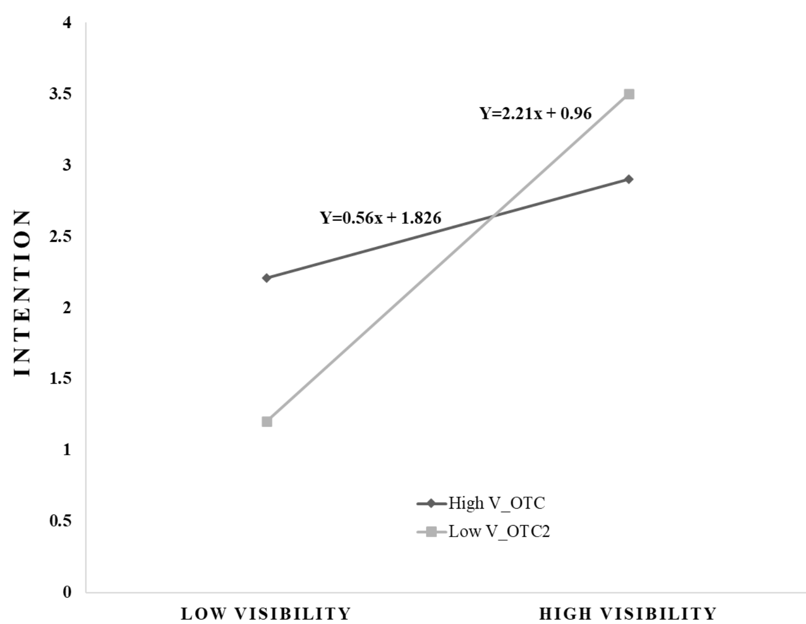

Figure 4. Moderation Influence of OTC on VIS-INT Relationship

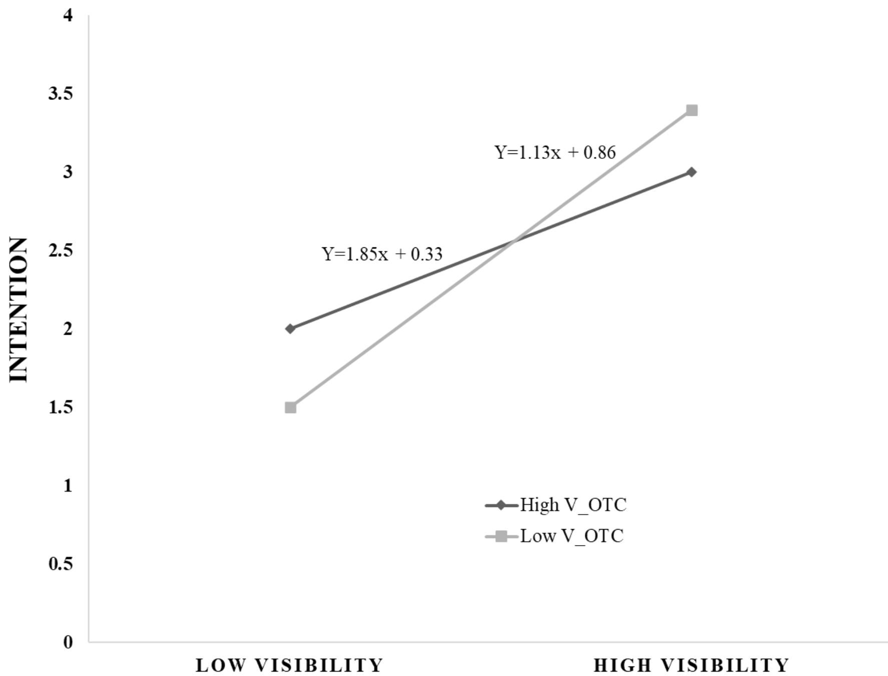

Figure 5. Moderation Influence of Gender on VIS-INT Relationship

6 Discussion

The active visibility of healthcare applications significantly influences individuals' intentions to use healthcare technologies (0.694, p<0.001). Increased visibility enhances awareness and perceived benefits, which positively enhances users' attitudes toward using healthcare technology (Zhang et al., 2014). Visibility also builds trust, which is a crucial factor in the healthcare industry. Furthermore, endorsements, testimonials, and transparent information reassure users about reliability, further encouraging adoption (Schultz & Kumar, 2024). Together, awareness, perceived benefits, and trust shape users' adoption intentions (Gao et al., 2015). However, demographic differences highlight the need for tailored visibility strategies that balance awareness and trust with the evolving technology and promote adoption. Another realm of visibility can be unlocked while we consider deriving a relationship with the individual's consumption values. Our study identifies a significant positive relationship between visibility and four consumption values—Functional Value (0.321, p<0.001), Conditional Value (0.246, p<0.001), Social Value (0.698, p<0.001), and Emotional Value (0.12, p<0.001)—but no significant link with Epistemic Value. These findings highlight how visibility shapes user beliefs and intentions toward adopting digital healthcare applications. Visibility enhances Functional Value by raising awareness of practical benefits as a key that drives adoption (Hung & Jen, 2012). Visibility also impacts Conditional Value by emphasizing relevance in specific scenarios, such as emergencies, reinforcing its role in contextualizing utility (Sweeney & Soutar, 2001). The strongest relationship was with Social Value, as visible healthcare applications symbolize modernity and health-conscious behavior, consistent with studies on technology's role in social signaling (Iyanna et al., 2022; Pundziene et al., 2023). Emotional Value is positively influenced by visibility, fostering familiarity and reducing apprehension, which builds trust and affinity—critical in healthcare contexts (Hung & Jen, 2012). However, visibility had no significant effect on Epistemic Value, as healthcare applications prioritize routine functionality over novelty or intellectual engagement. This aligns with previous findings that routine-oriented technologies lack the exploratory qualities needed for Epistemic Value (Berlyne, 1960; Sheth et al., 1991).

These results emphasize the multifaceted role of visibility in shaping consumption values and driving technology adoption. Developers and marketers should focus on visibility strategies that highlight practical, social, and emotional benefits while addressing privacy and trust concerns. Although visibility significantly enhances most consumption values, its limited impact on Epistemic Value suggests an area for future innovation (Gao et al., 2015; Kasilingam, 2020; Perrea et al., 2015). These consumption values, further magnify a person's intent towards adopting these evolving technologies.

Our study highlights the critical role of consumption values in shaping intentions to adopt healthcare applications. Functional value, conditional value, and emotional value showed significant positive associations with adoption intention, while social and epistemic values were not significant. These findings offer insights into the drivers of adoption and areas for enhancing appeal. The relationship between functional value and intention to adopt (0.201, $p<0.001$) underscores the importance of practical utility, such as facilitating appointment scheduling, health monitoring, and record management. This aligns with the Technology Acceptance Model (Davis, 1989), which emphasizes perceived usefulness as a key predictor of technology adoption. Other studies (e.g., Swan et al., 2024; Kim & Park, 2012; Sweeney & Soutar, 2001) further confirm the importance of reliable, practical benefits in driving user behavior. Conditional value (0.241, $p<0.003$) reflects the influence of situational factors, such as emergencies or seasonal health needs, on adoption. Applications designed to address specific scenarios are perceived as highly relevant, motivating users to adopt them (Sweeney & Soutar, 2001). This highlights the need for developers to consider diverse use cases and tailor functionalities accordingly. Emotional value (0.209, $p<0.059$) shows a weaker but significant relationship, suggesting that comfort, trust, and satisfaction positively influence adoption. Frequent positive interactions with applications foster emotional bonds, encouraging integration into daily life (Hung & Jen, 2012). User-centric designs that evoke positive emotions remain important despite their lesser impact compared to functional and conditional values. Social value did not significantly influence adoption, as users prioritize practical and situational benefits over social signaling. This finding aligns with studies indicating that social value plays a lesser role in healthcare contexts compared to other technology types, such as luxury or entertainment (Iyanna et al., 2022). Epistemic value was also non-significant, as healthcare applications lack the novelty or intellectual stimulation required to appeal to users seeking epistemic satisfaction. Technologies focused on routine tasks tend to prioritize functionality over exploration or intellectual engagement (Peng et al., 2016). These findings suggest that functional enhancements, tailored situational features, and trust-building through user-friendly designs are key to encouraging adoption. Efforts to leverage social and epistemic values may have limited impact in healthcare, where personal health needs take precedence.

This study offers a robust framework for understanding and influencing adoption in the healthcare technology sector by further understanding the mediating role of Consumption Values in the Visibility-Intention relationship (Davis, 1989; Duarte & Pinho, 2019). The adoption of healthcare applications is significantly mediated by users' values, specifically technology affinity (Emotional value), privacy perception (Conditional value), and perceived usefulness (functional value), while the impact of social status and curiosity on this relationship is negligible. These values induce appetite and catalyze the relationship between visibility-intention. Users with high technology affinity and perceived usefulness towards healthcare technologies are more likely to perceive healthcare applications as useful and easy to use, enhancing their adoption intentions (Davis, 1989; Venkatesh et al., 2003). Moreover, robust privacy measures can mitigate users' concerns, thereby increasing their willingness to adopt these technologies (Angst & Agarwal, 2009; Bansal et al., 2010). Conversely, the expected influence of social status via the visibility of application use does not significantly affect adoption rates which also synergizes with the past literature (Li et al., 2016). Thus, fostering technology affinity and ensuring privacy protections are crucial mediating factors (confidence level: 90%) for promoting the adoption of healthcare applications.

Furthermore, the relationship between visibility and the intention to adopt healthcare applications is moderated by an individual's openness to change, a trait associated with curiosity, flexibility, and a preference for novelty (McCrae & Costa, 1997; Oliver & Srivastava, 1999). This is a trait of early adopters, where openness to change is irrespective of the various extrinsic values that impact decision making toward healthcare technology (Chong & Moore, 2008). Individuals high in openness to change are intrinsically motivated to explore new technologies and often adopt innovations based on personal interest rather than external social cues, like visibility (Carter & Yeo, 2016; Li et al., 2016). This intrinsic motivation reduces the impact of visibility, as these users rely less on visible endorsements and more on their independent and spontaneous evaluation of the technology (Chong & Moore, 2008; Fygenson et al., 2006). Moreover, research has also highlighted that individuals who are open to change are less affected by extrinsic trends, instead focusing on innovation compatibility and potential personal growth, which further weakens the visibility-intention relationship (Hirt & Cheung, 2007).

Along with the openness to change with the evolving technologies, our study also found that gender differences play a significant moderating role in the visibility-adoption relationship, with research indicating that women typically exhibit more caution when approaching new technology due to greater concerns about security and data privacy (Gefen & Straub, 1997; Trauth, 2002). This cautious stance can lead women to weigh other factors, such as safety and usability, more heavily than visibility, reducing its influence on their adoption intentions (Colley & Comber, 2003; Hoque, 2016; Ilie et al., 2005; Zhang et al., 2014). Studies also suggest that women are less likely than men to adopt technology based on perceived social endorsement, instead preferring a more pragmatic evaluation of its value and trustworthiness (Ong & Lai, 2006; Trauth, 2002). This difference highlights the importance of addressing gender-specific adoption motivators, as the visibility of healthcare applications may not resonate as strongly with women, who tend to prioritize technology's practical and security aspects over its social visibility (Fisher & Margolis, 2002; Ong & Lai, 2006). Thus, our study supports the moderating impact of gender differences on technology adoption research.

6.1 Theoretical Implications

Prior studies have used unidimensional theories like TPB (Ajzen et al., 2015), TAM (Davis, 1989), and UTAUT (Venkatesh et al., 2003), which posed various gaps like an overemphasis on cognitive and behavioral factors, often neglecting the broader socio-organizational and cultural contexts that influence technology adoption, particularly in the healthcare sector (Venkatesh, 2022). Additionally, TAM has been criticized for its simplistic approach, which may fail to capture the complexity of adoption behaviors (Tarhini et al., 2015). Both TAM and UTAUT focus primarily on individual-level perceptions, overlooking the multifaceted nature of adoption factors such as emotional, social, and conditional consumption values (Venkatesh et al., 2003; Venkatesh & Bala, 2008). This study addresses the void of incorporating the individual's value system by integrating the Theory of Consumption Values (TCV), offering a holistic view that includes not only functional but also emotional, social, and conditional drivers. It expands beyond individual perceptions to account for broader contextual influences, thus providing a more comprehensive understanding of digital healthcare adoption. The findings also extend the TCV framework by incorporating visibility as an antecedent tool towards adoption intention. Additionally, moderating variables such as openness-to-change (OTC) and gender also highlight an individualistic perception of their adoption intentions (Colley & Comber, 2003; Hoque, 2016; Ong & Lai, 2006; Trauth, 2002). These insights also highlight that adoption intentions are not universally influenced but are contingent on individual traits (Lin & Huang, 2012) and demographic factors, thus enriching the theoretical discourse around TCV. Furthermore, the nuanced understanding of how visibility interacts with these values, amplifying some while dampening others, underscores the dual-edged nature of visibility in shaping adoption intentions.

6.2 Implications for Practitioners and Policymakers

This research offers valuable insights for healthcare providers, marketers, policymakers, and technology developers who want to increase the adoption of digital healthcare technologies. Our research showed that visibility plays a crucial role in shaping perceptions of emotional connection, functionality, social status, and trust which all influence consumer adoption of digital healthcare technologies (Piwek et al., 2016). However, increased visibility also raises privacy concerns and the need for data protection, particularly regarding how personal data is handled. Healthcare marketers must proactively educate consumers on privacy protections and security features to build consumer confidence and reduce adoption hesitation. In addition, healthcare marketing professionals should strategically leverage visibility through trusted channels like healthcare influencers, medical professionals, and patient advocacy groups. Campaigns should highlight both functional and emotional benefits demonstrating how digital healthcare solutions improve quality of life while ensuring data security and reliability (Duarte & Pinho, 2019). Using case studies, interactive content, and testimonials can enhance consumer trust and emotional engagement through effective storytelling.

Technology developers should focus on user-centered designs that prioritize usability but do not compromise privacy. This approach will ensure digital health solutions align with consumer expectations (Matthew-Maich et al., 2016). Our finding that there are gender-based differences in the adoption of digital health solutions shows the need for personalized marketing approaches. Female consumers tend to be more calculative, which requires more evidence-based assurances about reliability and privacy, making data-driven campaigns more effective. In contrast, male consumers are more spontaneous and may respond better to marketing that emphasizes cutting-edge technology, ease of use, and innovation**.** Additionally, the dampening effect of OTC on visibility-driven adoption suggests that this kind of targeted messaging could improve adoption outcomes. Campaigns that emphasize empowerment, long-term benefits, and societal impact can help reduce resistance among less open consumers (Jokisch et al., 2022). Healthcare marketing should also highlight how digital healthcare tools integrate seamlessly into everyday life**,** making them accessible and easy to use for diverse consumer segments.

7 Limitations and Future Directions

Despite its contributions, this study has certain limitations. The cross-sectional design restricts causal inferences, and future research could employ longitudinal studies or experimental designs to establish causality. Additionally, the focus on consumers already exposed to digital healthcare technologies may not fully capture the perspectives of non-users or late adopters. Broadening the sample to include diverse user groups would provide a more comprehensive understanding of adoption behaviors. While this study focuses on OTC and gender as key individual differences moderating the effect of visibility on adoption intention, future research could explore how contextual factors such as cultural norms and organizational influences shape this relationship. Examining these factors could provide deeper insights into whether personality-based or environmental influences play a more dominant role in driving technology adoption across different settings (Kessel et al., 2023). Future studies can also explore new designs that test tailored and specific visibility strategies, gauging their efficiency to improve adoption rates. Extending the analysis to other emerging technologies within and beyond healthcare contexts could further validate and refine the application of TCV in technology adoption research. Researchers can also study the impact of other values as suggested in the Shwartz theory that can work as moderators in place of OTC or a combination of these values collectively (Schwartz, 2012). This will give a newer perspective to this model since this theory can then be redesigned basis the scope of the study. By addressing these limitations and exploring new dimensions, future research can build upon this study's findings to advance the discourse on healthcare technology adoption and provide more personalized, context-specific strategies for driving adoption.

To conclude, this study accentuates the critical role of visibility in shaping individuals' intentions to adopt healthcare applications. Our findings establish that visibility suggestively influences four key consumption values—Functional, Conditional, Social, and Emotional—while having no impact on Epistemic Value (Lin & Huang, 2012; Kim & Park, 2012). The study highlights that visibility enhances awareness, perceived benefits, and trust, which collectively drive adoption intention (Chuah et al., 2016; Josiassen & Assaf, 2013). However, the differential impact of visibility on consumption values suggests that tailored visibility strategies are essential to maximize user engagement and adoption.

Additionally, our research contributes to the theoretical understanding of healthcare technology adoption by integrating the Theory of Consumption Values (TCV) into the visibility-intention framework. Unlike traditional adoption models such as TAM (Davis, 1989) and UTAUT (Alsyouf & Abdullah, 2018), which primarily emphasize cognitive and behavioral aspects, our study integrates emotional and circumstantial drivers, offering a more holistic perspective on adoption intentions. Furthermore, the moderating roles of openness to change (McCrae & Costa, 1997) and gender differences (Gefen & Straub, 1997) reveal that adoption intentions are not uniform but contingent on individual traits and demographic factors as well.

From a practical standpoint, our study provides actionable insights for healthcare technology developers and policymakers. Visibility strategies should not only highlight functional and conditional benefits but also build conviction and emotional kinship (Bagozzi et al., 1999; Holbrook & Batra, 1987). Privacy and security concerns must be addressed, particularly for female users who exhibit greater caution toward newer technology (Bansal et al., 2010). Moreover, the limited role of Social and Epistemic Values suggests that adoption efforts should focus on concrete, utility-driven benefits rather than novelty or social stimulus (Claudy et al., 2013). The findings thereby suggest an enhancing necessity towards tailored visibility strategies that align with different user motivations, providing actionable insights for marketers, developers, and healthcare service providers.

Despite its contributions, this study has certain limitations. The cross-sectional design limits fundamental implications, and future research should employ longitudinal studies to validate these findings. Additionally, intensifying the study to incorporate non-users or late adopters could provide a more inclusive understanding of adoption intentions (Iyanna et al., 2022). Future research could also explore additional moderating factors, such as cultural and socioeconomic influences, to refine the application of TCV in healthcare technology adoption. Addressing these aspects will enhance the generalizability of our findings and further enrich the discourse on digital healthcare adoption.

References

Abernethy, A., Adams, L., Barrett, M., Bechtel, C., Brennan, P., Butte, A., Faulkner, J., Fontaine, E., Friedhoff, S., Halamka, J., Howell, M., Johnson, K., Long, P., McGraw, D., Miller, R., Lee, P., Perlin, J., Rucker, D., Sandy, L., Savage, L., Stump, L., Tang, P., Topol, E., Tuckson, R., & Valdes, K. (2022). The promise of digital health: Then, now, and the future. *NAM Perspectives, 6*(22).

Abma, T. A., Visse, M., Hanberger, A., Simons, H., & Greene, J. C. (2020). Enriching evaluation practice through care ethics. *Evaluation, 26*(2), 131–146.

Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences, 28*(3), 557–582.

Ajzen, I. (2012). The theory of planned behavior. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology: Volume 1* (pp. 438–459). SAGE Publications Ltd.

Alsyouf, A., & Abdullah, O. Y. (2018). Understanding EHRs continuance intention to use from the perspectives of UTAUT: Practice environment moderating effect and top management support as predictor variables. *International Journal of Electronic Healthcare, 10*.

Amos, C., Brockhaus, S., Fawcett, A. M., Fawcett, S. E., & Knemeyer, A. M. (2019). Blinded by the light? Analyzing sustainability authenticity, customer service perceptions, and halo effects. *The International Journal of Logistics Management, 30*(1), 117–139.

Angst, C. M., & Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *MIS Quarterly, 33*(2), 339–370.

Aschemann-Witzel, J., & Niebuhr Aagaard, E. M. (2014). Elaborating on the attitude-behaviour gap regarding organic products: Young Danish consumers and in-store food choice. *International Journal of Consumer Studies, 38*(5), 550–558.

Bagozzi, R. P., Gopinath, M., & Nyer, P. U. (1999). The role of emotions in marketing. *Journal of the Academy of Marketing Science, 27*(2), 184–206.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bansal, G., Zahedi, F. M., & Gefen, D. (2010). The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online. *Decision Support Systems, 49*(2), 138–150.

Berlyne, D. E. (1960). Stimulus selection and conflict. In *Conflict, arousal, and curiosity* (pp. 1–17). McGraw-Hill.

Butcher, C. J., & Hussain, W. (2022). Digital healthcare: The future. *Future Healthcare Journal, 9*(2), 113–117.

Carter, S., & Yeo, A. C.-M. (2016). Mobile apps usage by Malaysian business undergraduates and postgraduates. *Internet Research, 26*(3), 733–757.

Chakraborty, S., Bhatt, V., Chakravorty, T., & Chakraborty, K. (2021). Analysis of digital technologies as antecedent to care service transparency and orchestration. *Technology in Society, 65*, 101568.

Chau, P. Y. K., & Hu, P. J. (2002). Examining a model of information technology acceptance by individual professionals: An exploratory study. *Journal of Management Information Systems, 18*(4), 191–229.

Chaudhuri, A., & Holbrook, M. B. (2001). The chain of effects from brand trust and brand affect to brand performance: The role of brand loyalty. *Journal of Marketing, 65*(2), 81–93.

Chen, K., & Chan, A. H. S. (2011). A review of technology acceptance by older adults. *Gerontechnology, 10*(1), 1–12.

Choe, J. Y. J., & Kim, S. S. (2019). Development and validation of a multidimensional tourist's local food consumption value (TLFCV) scale. *International Journal of Hospitality Management, 77*, 245–259.

Choi, J., & Kim, S. (2016). Is the smartwatch an IT product or a fashion product? A study on factors affecting the intention to use smartwatches. *Computers in Human Behavior, 63*, 777–786.

Chong, T. C., & Moore, G. A. (2008). *Crossing the chasm: Marketing and selling disruptive products to mainstream customers*. Recommended Reference Books for Technology Marketers.

Chuah, S. H. W., Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: The role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior, 65*, 276–284.

Cialdini, R. B., & Trost, M. R. (1998). Social norms, conformity and compliance. In D. T. Gilbert, S. T. Fiske, & G. Lindzey (Eds.), *The handbook of social psychology* (Vol. 2, pp. 151–192). McGraw-Hill.

Claudy, M. C., Peterson, M., & O'Driscoll, A. (2013). Understanding the attitude-behavior gap for renewable energy systems using behavioral reasoning theory. *Journal of Macromarketing, 33*(4), 273–287.

Colley, A., & Comber, C. (2003). Age and gender differences in computer use and attitudes among secondary school students: What has changed? *Educational Research, 45*(2), 155–165.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–339.

Dhir, A., Koshta, N., Goyal, R. K., Sakashita, M., & Almotairi, M. (2021). Behavioral reasoning theory (BRT) perspectives on E-waste recycling and management. *Journal of Cleaner Production, 280*, 124269.

Dinh, T. C. T., & Lee, Y. (2024). Social media influencers and followers' conspicuous consumption: The mediation of fear of missing out and materialism. *Heliyon, 10*(16), e26198.

Duarte, P., & Pinho, J. C. (2019a). A mixed methods UTAUT2-based approach to assess mobile health adoption. *Journal of Business Research, 102*, 140–150.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451–474.

Fisher, A., & Margolis, J. (2002). Unlocking the clubhouse. *ACM SIGCSE Bulletin, 34*(2), 79–83.

Fygenson, M., & Anderson, P. A. P. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly, 30*(1), 115–143.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research, 18(1), 39-50.

Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems, 115*(9), 1704–1723.

Gefen, D., & Straub, D. W. (1997). Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly, 21*(4), 389–400.

Ginsburg, G. S., Picard, R. W., & Friend, S. H. (2024). Key issues as wearable digital health technologies enter clinical care. *New England Journal of Medicine, 390*(12), 1118–1127.

Gopinath, K., Selvam, G., & Narayanamurthy, G. (2022). Determinants of the adoption of wearable devices for health and fitness: A meta-analytical study. *Communications of the Association for Information Systems, 50*(1), 23.

Grand View Research. (2024). *Digital health market size, share & trends analysis report by technology (Healthcare analytics, mHealth), by component (Hardware, software, services), by application, by end-use, by region, and segment forecasts, 2024–2030*. Retrieved from https://www.grandviewresearch.com/industry-analysis/digital-health-market

Guo, X., Zhang, X., & Sun, Y. (2016). The privacy-personalization paradox in mHealth services acceptance of different age groups. *Electronic Commerce Research and Applications, 16*, 55–65.

Habibi, A., Yusop, F. D., & Razak, R. A. (2020). The dataset for validation of factors affecting pre-service teachers' use of ICT during teaching practices: Indonesian context. *Data in Brief*, *28*, 104875

Hair, J. F., Jr., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). *European Business Review, 26*(2), 106–121.

Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly, 31*(4), 705–737.

Holbrook, M. B., & Batra, R. (1987). Assessing the role of emotions as mediators of consumer responses to advertising. *Journal of Consumer Research, 14*(3), 404–420.

Holden, R. J., & Karsh, B.-T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics, 43*(1), 159–172.

Hoque, M. R. (2016). An empirical study of mHealth adoption in a developing country: The moderating effect of gender concern. *BMC Medical Informatics and Decision Making, 16*(1), 51.

Hung, M. C., & Jen, W. Y. (2012). The adoption of mobile health management services: An empirical study. *Journal of Medical Systems, 36*(3), 1381–1388.

Hur, K., Kim, T. T., Karatepe, O. M., & Lee, G. (2017). An exploration of the factors influencing social media continuance usage and information sharing intentions among Korean travellers. *Tourism Management, 63*, 170–178.

Ilie, V., Green, G., & Lou, H. (2005). Gender differences in perceptions and use of communication technologies: A diffusion of innovation approach. *Information Resources Management Journal, 18*(3), 13–20.

Iyanna, S., Kaur, P., Ractham, P., Talwar, S., & Najmul Islam, A. K. M. (2022). Digital transformation of healthcare sector: What is impeding adoption and continued usage of technology-driven innovations by end-users? *Journal of Business Research, 153*, 150–161.

Jandoo, T. (2020). WHO guidance for digital health: What it means for researchers. *Digital Health, 6*, 1–5.

Johnson, V. L., Kiser, A., Washington, R., & Torres, R. (2018). Limitations to the rapid adoption of m-payment services: Understanding the impact of privacy risk on m-payment services. *Computers in Human Behavior, 79*, 111–122.

Jokisch, M. R., Schmidt, L. I., & Doh, M. (2022). Acceptance of digital health services among older adults: Findings on perceived usefulness, self-efficacy, privacy concerns, ICT knowledge, and support seeking. *Frontiers in Public Health, 10*, 889012.

Josiassen, A., & Assaf, A. G. (2013). Look at me—I am flying: The influence of social visibility of consumption on tourism decisions. *Annals of Tourism Research, 40*(1), 155–175.

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society, 62*, 101280.

Kessel, R. van, Kyriopoulos, I., & Wouters, B. (2023). The effect of the COVID-19 pandemic on digital health–seeking behavior: Big data interrupted time-series analysis of Google Trends. *Journal of Medical Internet Research*, *25*, e42401.

Kilgus, T., Patecka, A., Schurig, T., Kari, A., Gubser, R., Gersch, M., ... & Fürstenau, D. (2024). Creating value from the secondary use of health data: International examples, best practices, and opportunities to scale. *Communications of the Association for Information Systems, 55*(1), 20.

Kim, J., & Park, H. A. (2012). Development of a health information technology acceptance model using consumers' health behavior intention. *Journal of Medical Internet Research, 14*(5).

Kim, K. J., & Shin, D.-H. (2015). An acceptance model for smart watches. *Internet Research, 25*(4), 527–541.

Kim, S. S., & Malhotra, N. K. (2005). Predicting system usage from intention and past use: Scale issues in the predictors. *Decision Sciences, 36*(1), 187–196.

Kim, S., & Garrison, G. (2009). Investigating mobile wireless technology adoption: An extension of the technology acceptance model. *Information Systems Frontiers, 11*(3), 323–333.

Kuo, K. M., Liu, C. F., & Ma, C. C. (2013). An investigation of the effect of nurses' technology readiness on the acceptance of mobile electronic medical record systems. *BMC Medical Informatics and Decision Making, 13*(1).

Li, H., Wu, J., Gao, Y., & Shi, Y. (2016). Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *International Journal of Medical Informatics, 88*, 8–17.

Lin, P.-C., & Huang, Y.-H. (2012). The influence factors on choice behavior regarding green products based on the theory of consumption values. *Journal of Cleaner Production, 22*(1), 11–18.

Matthew-Maich, N., Harris, L., Ploeg, J., Markle-Reid, M., Valaitis, R., Ibrahim, S., Gafni, A., & Isaacs, S. (2016). Designing, implementing, and evaluating mobile health technologies for managing chronic conditions in older adults: A scoping review. *JMIR MHealth and UHealth, 4*(2), e29.

McCrae, R. R., & Costa, P. T. (1997). Personality trait structure as a human universal. *American Psychologist, 52*(5), 509–516.

Meuter, M. L., McCabe, D. B., & Curran, J. M. (2013). Electronic word-of-mouth versus interpersonal word-of-mouth: Are all forms of word-of-mouth equally influential? *Services Marketing Quarterly, 34*(3), 240–256.

Myyry, L., Siponen, M., Pahnila, S., Vartiainen, T., & Vance, A. (2009). What levels of moral reasoning and values explain adherence to information security rules? An empirical study. *European Journal of Information Systems, 18*(2), 126–139.

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality and Quantity, 41*(5), 673–690.

Oliver, J. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (2nd ed., pp. 102–138). Guilford Press.

Ong, C. S., & Lai, J. Y. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Computers in Human Behavior, 22*(5), 816–829.

Pai, F. Y., & Huang, K. I. (2011). Applying the technology acceptance model to the introduction of healthcare information systems. *Technological Forecasting and Social Change, 78*(4), 650–660.

Papadopoulos, K., Von Wyl, V., & Gille, F. (2024). What is public trust in national electronic health record systems? A scoping review of qualitative research studies from 1995 to 2021. *Digital Health, 10*, 20552076241228024.

Park, G. E., Park, Y. H., Kim, K. G., Park, J. Y., Hwang, M., & Lee, S. (2024). Mobile application for digital health coaching in the self-management of older adults with multiple chronic conditions: A development and usability study. *Healthcare Informatics Research, 30*(4), 344–354.

Peng, W., Kanthawala, S., Yuan, S., & Hussain, S. A. (2016). A qualitative study of user perceptions of mobile health apps. *BMC Public Health, 16*(1), 1–11.

Perrea, T., Grunert, K. G., & Krystallis, A. (2015). Consumer value perceptions of food products from emerging processing technologies: A cross-cultural exploration. *Food Quality and Preference, 39*, 95–108.

Petrescu, M., Kachen, S., Dobre, C., Milovan-Ciuta, A., & Orzan, M. (2024). Decoding the dual desire: Expressive and impressive motivations for neo-luxury wearables. *Journal of Marketing Communications*, 1–22.

Piwek, L., Ellis, D. A., Andrews, S., & Joinson, A. (2016). The rise of consumer health wearables: Promises and barriers. *PLoS Medicine, 13*(2), e1001953.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63*, 539–569.

Poleacovschi, C., & Javernick-Will, A. (2020). The importance of expertise visibility across organizational boundaries for individual performance. *Engineering Management Journal, 32*(1), 37–45.

Pundziene, A., Sermontyte-Baniule, R., Rialp-Criado, J., & Chesbrough, H. (2023). Indirect effect of open innovation on clinical and economic value creation in digital healthcare: A comparative study of European countries. *Journal of Business Research, 159*, 113701.

Pura, M. (2005). Linking perceived value and loyalty in location-based mobile services. *Managing Service Quality: An International Journal, 15*(6), 509–538.

Rivière, J.-P., Jacob, F., & Girard, A. (2024). Using patient experiences to understand the (missed) digitalisation of the public health service. *Journal of Marketing Management, 40*(11–12), 968–995.

Rogers, E. M. (1995). Lessons for guidelines from the diffusion of innovations. *The Joint Commission Journal on Quality Improvement, 21*(7), 324–328.

Rydell, R. J., & McConnell, A. R. (2006). Understanding implicit and explicit attitude change: A systems of reasoning analysis. *Journal of Personality and Social Psychology, 91*(6), 995–1008.

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128*, 13–35.

Schmitt, B. (1999). Experiential marketing. *Journal of Marketing Management, 15*(1–3), 53–67.

Schultz, C. D., & Kumar, H. (2024). ARvolution: Decoding consumer motivation and value dimensions in augmented reality. *Journal of Retailing and Consumer Services, 78*, 103701.

Schwartz, S. H. (2012). An overview of the Schwartz theory of basic values. *Online Readings in Psychology and Culture, 2*(1), 11.

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. *Journal of Business Research, 22*(2), 159–170.

Silvera-Tawil, D. (2024). Robotics in healthcare: A survey. SN Computer Science, 5(1), 189.

Sun, J., Wang, Y., & Rodriguez, N. (2013). Health digital inclusion and patient-centered care readiness in the USA. *Communications of the Association for Information Systems, 32*(1), 8.

Swan, E. L., Peltier, J. W., & Dahl, A. J. (2024). Artificial intelligence in healthcare: The value co-creation process and influence of other digital health transformations. *Journal of Research in Interactive Marketing, 18*(1), 109–126.

Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing, 77*(2), 203–220.

Sze, K. P., Fong, Q. W., De Roza, J. G., Lee, E. S., & Tan, S. Y. (2024). Exploring physicians' perceptions of digital health's impact on the patient-physician relationship in the primary health care setting: Qualitative descriptive study. *Journal of Medical Internet Research, 26*, e53705.

Talukder, M., & Quazi, A. (2011). The impact of social influence on individuals' adoption of innovation. *Journal of Organizational Computing and Electronic Commerce, 21*(2), 111–135.

Talwar, S., Talwar, M., Kaur, P., & Dhir, A. (2020). Consumers' resistance to digital innovations: A systematic review and framework development. *Australasian Marketing Journal, 28*(4), 286–299.

Tandon, A., Kaur, P., Bhatt, Y., Mäntymäki, M., & Dhir, A. (2021). Why do people purchase from food delivery apps? A consumer value perspective. *Journal of Retailing and Consumer Services, 63*, 102667.

Tanrikulu, C. (2021). Theory of consumption values in consumer behaviour research: A review and future research agenda. *International Journal of Consumer Studies, 45*(6), 1176–1197.

Tarhini, A., Arachchilage, N. A. G., Masa'deh, R., & Abbasi, M. S. (2015). A critical review of theories and models of technology adoption and acceptance in information system research. *International Journal of Technology Diffusion, 6*(4), 58–77.

Taylor, S., & Todd, P. (1995). Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. *International Journal of Research in Marketing, 12*(2), 137–155.

Thomson, M., MacInnis, D. J., & Park, C. W. (2005). The ties that bind: Measuring the strength of consumers' emotional attachments to brands. *Journal of Consumer Psychology, 15*(1), 77–91.

Trauth, E. M. (2002). Odd girl out: An individual differences perspective on women in the IT profession. *Information Technology & People, 15*(2), 98–118.

Truong, Y., & McColl, R. (2011). Intrinsic motivations, self-esteem, and luxury goods consumption. *Journal of Retailing and Consumer Services, 18*(6), 555–561.

Turel, O., Serenko, A., & Bontis, N. (2010). User acceptance of hedonic digital artifacts: A theory of consumption values perspective. *Information & Management, 47*(1), 53–59.

Turner, J. C., & Oakes, P. J. (1986). The significance of the social identity concept for social psychology with reference to individualism, interactionism and social influence. *British Journal of Social Psychology, 25*(3), 237–252.

Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research, 308*(1–2), 641–652.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315.

Venkatesh, V., & Davis, F. D. (2000). Theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Vesselkov, A., Hämmäinen, H., & Töyli, J. (2019). Design and governance of mHealth data sharing. *Communications of the Association for Information Systems, 45*, 299–321.

Wu, K.-W., Huang, S. Y., Yen, D. C., & Popova, I. (2012). The effect of online privacy policy on consumer privacy concern and trust. *Computers in Human Behavior, 28*(3), 889–897.

Yadav, R., Giri, A., & Chatterjee, S. (2022). Understanding the users' motivation and barriers in adopting healthcare apps: A mixed-method approach using behavioral reasoning theory. *Technological Forecasting and Social Change, 183*, 121932.

Zafar, H., & Sneha, S. (2012). Ubiquitous healthcare information system: Toward crossing the security chasm. *Communications of the Association for Information Systems, 31*(1), 9.

Zhang, X., Guo, X., Lai, K. H., Guo, F., & Li, C. (2014). Understanding gender differences in m-health adoption: A modified theory of reasoned action model. *Telemedicine and E-Health, 20*(1), 39–46.

Zollo, L., Filieri, R., Rialti, R., & Yoon, S. (2020). Unpacking the relationship between social media marketing and brand equity: The mediating role of consumers' benefits and experience. *Journal of Business Research, 117*, 256–267.

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