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The Social Psychology of Adopting AI-Based Health Sensors: Insights from a Qualitative Study

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Abstract

This study investigates users' perceptions and acceptance of AI-integrated radar health monitoring devices by applying an extended Technology Acceptance Model (TAM)–Protection Motivation Theory (PMT) framework. While previous research has largely relied on survey-based data, this study employs a quantitative content analysis using NVivo to examine linguistic expressions of user attitudes toward AI-enabled health technologies. Data were collected from 15 participants who viewed a demonstration video of the device, and their feedback was systematically coded into four refined themes: Perceived Ease and Usefulness (PEU), Attitude and Intention toward Use (ATI), Health Risk Perception (HRP), and Perceived Risk (PR). Frequency and thematic analyses revealed that PEU was the most dominant factor influencing user acceptance, followed by ATI and HRP, while PR appeared less prominent but remained a moderating concern. The findings highlight that users' acceptance is shaped by a balance between functional confidence, emotional reassurance, and ethical trust in AI. The study contributes theoretically by extending the TAM–PMT model through linguistic quantification, demonstrating how perceived usability and health motivation jointly influence technology adoption. Managerially, it provides insights for developers and policymakers on improving usability, transparency, and risk communication in AI-based healthcare systems.

Keywords: AI healthcare; Radar sensor; User perception

1. Introduction

In 2025, the U.S. Centers for Disease Control and Prevention (CDC) released its Vision for Using Artificial Intelligence in Public Health, emphasizing the transformative capacity of AI and machine learning to enhance operational efficiency, prevent disease, and strengthen data-driven decision-making within health systems (CDC, 2025). This vision mirrors a broader international shift toward embedding AI technologies into healthcare infrastructure to improve diagnostic precision, personalize treatment, and anticipate health risks before they escalate. The global non-invasive monitoring device market, valued at USD 21.5 billion in 2024, is projected to reach USD 36.39 billion by 2031, reflecting a compound annual growth rate (CAGR) of approximately 7% (Verified Market Research, 2024). This expansion is principally driven by growing demand for remote patient monitoring and the rising incidence of chronic diseases in aging populations. Consequently, AI-integrated radar sensors are emerging as key elements of digital health infrastructure, enabling early detection, personalized interventions, and real-time clinical decision-making.

AI-driven systems now assist in diagnostic decision-making, real-time patient monitoring, and predictive health management, offering new levels of precision and efficiency (Zeb et al., 2024). Among emerging technologies, radar-based sensors stand out for their ability to monitor vital signs such as heart rate and respiration remotely, eliminating the need for physical contact. Applications range from predictive analytics for disease prevention to real-time physiological monitoring across diverse devices (Guk et al., 2019). Prior studies further suggest that AI can minimize human error, enhance diagnostic reliability, and enable proactive medical interventions, outcomes that are especially vital amid aging populations and constrained healthcare resources (Sankaran & Singla, 2024; Faiyazuddin et al., 2025).

While the technological capabilities of AI systems are widely acknowledged, the literature continues to reveal significant gaps. Research has primarily concentrated on performance metrics, such as diagnostic accuracy, algorithmic robustness, and predictive validity, while giving insufficient attention to how users interpret, trust, and adopt these technologies

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(Faiyazuddin et al., 2025). These perceptual dimensions are often analyzed in isolation rather than as interrelated factors, for example, concerns about data reliability may amplify doubts about usability or fairness. Furthermore, emotional and ethical factors such as privacy concerns, data security, and perceived control often shape whether people view such devices as empowering tools or as intrusive technologies (Marikyan et al., 2024). These factors are particularly relevant in the case of radar-AI systems, which operate continuously and collect sensitive biometric data within private spaces.

The present study responds to this gap by investigating how AI in healthcare is discussed and perceived across stakeholder narratives through advanced text-mining approaches. To fill this gap, the present study adopts a quantitative content analysis using NVivo to examine how individuals linguistically construct their perceptions and intentions toward AI-integrated radar sensors in healthcare. Building upon the research model proposed by Wang et al. (2023), the research applies an extended version of the Technology Acceptance Model (TAM) that incorporates perceived credibility and perceived risk as additional determinants of user acceptance. This integrated framework captures not only the traditional cognitive factors, perceived usefulness (PU), perceived ease of use (PEOU), attitude toward use (AT), and behavioral intention (BI), but also the psychological and ethical dimensions of trust, privacy, and risk perception that critically influence technology adoption in healthcare.

By quantifying textual patterns from user interviews, the study identifies how these theoretical constructs are reflected in natural language through word frequency, co-occurrence, and conceptual clustering analyses within NVivo. This approach transforms qualitative discourse into measurable data, allowing a structured examination of how individuals cognitively and emotionally evaluate AI-enabled radar technologies. Through this model-driven lens, the study contributes to extending prior TAM-based research by providing empirical linguistic evidence of user acceptance and perceived credibility in the context of AI-assisted healthcare monitoring.

2. Literature Review

2.1. Artificial Intelligence in Healthcare

The integration of artificial intelligence (AI) into healthcare has marked a fundamental transformation in how medical data are analyzed, interpreted, and acted upon. AI technologies, ranging from diagnostic algorithms to predictive analytics, have demonstrated their capacity to enhance clinical decision-making, reduce human error, and improve the efficiency of healthcare (Alkhatib et al., 2025). In particular, non-contact sensing systems such as radar-based devices have emerged as a promising innovation, allowing continuous monitoring of vital signs such as heart rate and respiration without physical attachment (Kebe et al., 2020). This advancement enhances patient comfort and expands healthcare accessibility, particularly for aging individuals and those requiring long-term monitoring.

However, the successful adoption of AI-driven health technologies extends beyond technical performance; it also depends on users' psychological, behavioral, and ethical perceptions. Previous studies often emphasized algorithmic accuracy and clinical outcomes while overlooking how individuals perceive and interact with AI systems in everyday health contexts. To address this limitation, Wang et al. (2023) proposed an integrated theoretical framework that combines the Technology Acceptance Model (TAM), Protection Motivation Theory (PMT), and Perceived Risk Theory to explain user acceptance of mobile health technologies. The model highlights that acceptance behavior is influenced not only by cognitive beliefs, such as perceived usefulness (PU) and perceived ease of use (PEOU), but also by health-related motivations, including perceived susceptibility (PSu) and perceived severity (PSe), and risk perceptions surrounding privacy, trust, and technological credibility.

Building upon this framework, the present study applies these theories to the context of AI-integrated radar sensors in healthcare. This research employs quantitative content analysis in NVivo to examine how individuals linguistically articulate beliefs, concerns, and intentions regarding AI-enabled monitoring devices. The analysis identifies linguistic patterns and conceptual associations shaping perceptions of usefulness, ease of use, health vulnerability, and risk. This approach advances TAM-based inquiry by offering empirical evidence of cognitive and emotional meaning-making in AI healthcare contexts, complementing traditional survey methodologies.

2. 2. User Perceptions and Acceptance of AI in Healthcare

Understanding users' perceptions and acceptance of AI-based healthcare technologies has become a central issue in both technology adoption and health behavior research. The introduction of AI into medical contexts alters not only diagnostic and operational processes but also the psychological relationship between humans and technology. Users' acceptance is shaped by their trust in algorithmic systems, emotional comfort with automation, and perceived alignment between technology and personal health needs (Gerlich, 2023). This suggests that technological adoption in healthcare is not merely a rational decision but also a social and emotional negotiation involving beliefs, fears, and ethical considerations (Gerritse et al., 2022).

From a behavioral perspective, Technology Acceptance Model (TAM) (Davis, 1989) and Protection Motivation Theory (PMT) (Rogers, 1975) have been widely used to explain how individuals evaluate new healthcare technologies. TAM highlights the cognitive aspects of technology use, specifically perceived usefulness (PU) and perceived ease of use (PEOU), which influence users' attitudes and behavioral intentions. PMT, in turn, introduces motivational factors related to perceived susceptibility (PSu) and perceived severity (PSe) of health risks, explaining why individuals adopt technologies that enhance protection or prevention. In the healthcare domain, these frameworks are often complemented by the Perceived Risk Theory (Taylor, 1974), which emphasizes the role of uncertainty, privacy concerns, and trust in shaping user attitudes toward digital health systems.

Recent scholarship has shown that trust and transparency play pivotal roles in users' willingness to rely on AI for health-related decision-making. People's comfort with AI depends not only on its technical accuracy but also on its perceived empathy, fairness, and explainability (Shin, 2020). Users often experience ambivalence: while they value AI's efficiency and objectivity, they also express anxiety about its impersonal nature or potential to undermine human oversight (Oomen et al., 2024). For instance, individuals from highly digitized environments tend to exhibit stronger confidence in AI-driven health monitoring, whereas others may approach such technologies with skepticism due to concerns about data security and autonomy (Williamson & Prybutok, 2024).

2.3. User Perceptions and Acceptance of AI in Healthcare

Trust remains the cornerstone of public acceptance for AI technologies in healthcare (Shevtsova et al., 2024). Unlike conventional medical tools, AI systems engage in autonomous decision-making, requiring users to rely on algorithmic outputs that may not always be fully explainable. Users' confidence depends not only on the technical accuracy of AI but also on its ethical alignment with principles of beneficence, fairness, and accountability (Floridi et al., 2018). When AI systems demonstrate reliability, consistency, and regulatory approval, perceived risk decreases and behavioral intention to adopt increases (Hasan et al., 2021). Conversely, uncertainty about data processing or potential system errors can undermine trust, particularly among older or less tech-experienced users.

Transparency and explainability are equally critical in fostering trust. Users seek to understand how their data are processed and how AI reaches conclusions about health conditions. Igwe-Nmaju and Anadozie (2022) emphasize that IoT and AI health systems must ensure user comprehension and maintain open communication channels to enhance legitimacy and mitigate skepticism. Clear information about data handling, validation, and error rates not only builds trust but also reinforces users' sense of control and agency within technology-mediated healthcare (Bodó, 2021).

Ethical concerns, particularly privacy, data security, and algorithmic bias, remain major barriers to AI adoption. Given the sensitivity of health data, any breach or misuse can irreversibly undermine user trust. Studies highlight that concerns about surveillance, unequal data representation, and discrimination in AI models contribute to resistance among potential users (Mann & Matzner, 2019; Bircan & Özbilgin, 2025). Addressing these issues requires transparent data governance, inclusive model training, and adherence to ethical design frameworks that ensure fairness and accountability.

2.4. The Extended TAM–PMT Framework in Healthcare Technology Adoption

To better explain users' acceptance of intelligent healthcare technologies, Wang et al. (2023) proposed an integrated framework combining the Technology Acceptance Model (TAM) and the Protection Motivation Theory (PMT). This extended TAM–PMT framework enhances the explanatory power for behavioral intention by integrating cognitive technology evaluations with health-threat motivational factors. It preserves core TAM constructs (PEOU, PU, AT, BI) and incorporates perceived susceptibility, perceived severity, and perceived risk to capture protective motivation dynamics in AI-enabled healthcare contexts.

In addition to TAM and PMT, the Theory of Planned Behavior (Ajzen, 1991) provides a complementary psychological perspective that explains behavioral intention through three determinants: attitude toward behavior, subjective norms, and perceived behavioral control. In healthcare contexts, TPB has been applied to understand how individuals' beliefs, social influences, and self-efficacy shape their willingness to adopt digital and AI-based technologies. Integrating TPB enhances the theoretical foundation by connecting individual cognition with social and motivational dimensions of technology acceptance. This perspective aligns with the current study's focus on attitudes and intentions, highlighting how perceived ease, usefulness, and health motivation jointly influence behavioral intention to use AI-integrated radar sensors. Table 1 provides an overview of the key variables, their meanings, and the primary references supporting each construct

Table 1. Theoretical Constructs and Conceptual Definitions

Construct	Conceptual Definition	Key References
Perceived Ease of Use (PEOU)	The degree to which an individual believes that using a system would be free of physical or mental effort. It reflects simplicity, convenience, and clarity of interaction with the technology.	Davis (1989); Wang et al. (2023)

Perceived Usefulness (PU)	The degree to which a person believes that using a specific system will enhance their performance or achieve desired outcomes. In health contexts, it indicates perceived improvement in well-being and care quality.	Davis (1989); Wang et al. (2023)
Attitude toward Use (AT)	An individual's positive or negative evaluative feeling about using a particular technology. It represents an affective orientation that influences behavioral intention.	Ajzen (1991); Wang et al. (2023)
Behavioral Intention (BI)	The degree to which a person consciously plans or intends to perform a specific behavior, such as adopting or continuing to use a system.	Ajzen (1991); Wang et al. (2023)
Perceived Susceptibility (PSu)	The individual's subjective judgment about the likelihood of experiencing a health threat or condition. It reflects awareness of personal vulnerability.	Rogers (1975); Wang et al. (2023)
Perceived Severity (PSe)	The perceived seriousness of the consequences associated with a health threat. It represents the cognitive evaluation of potential harm to health or life.	Rogers (1975); Wang et al. (2023)
Perceived Risk (PR)	The individual's expectation of possible negative outcomes (e.g., errors, privacy violations, data misuse) when engaging with technology. It combines uncertainty and potential loss.	Taylor (1974); Wang et al. (2023)

2.5. Text-Mining Approaches in Healthcare Research

Text-mining has become an increasingly valuable approach for quantifying qualitative data such as interviews, reviews, or open-ended survey responses. In healthcare contexts, it enables researchers to identify how patients and users linguistically construct concepts such as trust, risk, and usefulness, dimensions that closely align with psychological constructs (Colombo et al., 2023).

Text-mining allows for a structured examination of natural language patterns, converting subjective narratives into measurable variables. Techniques such as word frequency analysis, co-occurrence mapping, and thematic coding facilitate the detection of relationships between emotional, cognitive, and ethical aspects of technology acceptance (Gutierrez et al., 2021).

Language offers insight into how people make sense of emerging health technologies. Text-mining provides a computational bridge between qualitative interpretation and large-scale data analysis, revealing how user express hopes, fears, and expectations about AI. It treats discourse as a social practice embedded in culture and emotion (Lupton, 2019). By examining linguistic patterns, researchers can trace how perceptions of AI, trust, risk, empathy, are produced and reproduced.

3. Methodology

3.1. Data Collection

This study employed a quantitative content analysis approach to examine how individuals linguistically express their perceptions and attitudes toward AI-integrated radar sensors in healthcare. Data were collected through semi-structured, in-depth interviews designed to elicit participants' reflections on their awareness, trust, and acceptance of radar-based health monitoring.

Fifteen interviews were conducted, generating approximately 8,300 words of transcribed text. Participants were asked to describe their understanding of AI in healthcare, perceived usefulness and usability of radar sensors, as well as their concerns regarding privacy, transparency, and data security. The interview guide was structured around key constructs from the extended TAM–PMT framework, ensuring alignment between data collection and theoretical focus.

3.2. Participants

A total of fifteen participants took part in this study. The sample size aligns with the recommendations of Guest et al. (2006), who found that thematic saturation in interview-based research is typically achieved after twelve participants, with minimal new insights emerging beyond that number. Participants were selected through purposive sampling to ensure diversity in demographic characteristics and levels of familiarity with digital and healthcare technologies.

All participants were invited to take part in the study voluntarily and provided informed consent prior to the interviews. The purpose of the research, the nature of participation, and confidentiality measures were clearly explained before data collection. Participants were informed that their personal information and responses would be used solely for academic purposes and would remain strictly confidential. No identifying details were recorded in the transcripts, and pseudonyms were assigned to protect anonymity. This ethical procedure ensured that all interviews complied with research integrity standards and respected participants' privacy and autonomy.

All participants were international students in Korea, reflecting diverse national, linguistic, and cultural backgrounds. This cohort was purposefully selected because international students typically exhibit high exposure to emerging technologies while retaining varied cultural perspectives on AI and privacy, offering rich linguistic variation and a wide range of perceptions for analysis. Participation was voluntary, with informed consent obtained prior to interviews. To ensure confidentiality, pseudonyms were assigned and all identifiable information was removed during transcription. Face-to-face interviews were conducted in English in quiet settings conducive to open reflection, lasted approximately 20 minutes, and explored participants' experiences, beliefs, and emotional responses regarding AI in healthcare.

3.3. Theme Refinement

A theme refinement procedure was undertaken prior to coding to ensure theoretical coherence and limit redundancy among overlapping constructs. The objective was to establish a concise and analytically consistent set of categories aligned with the extended TAM–PMT framework while preserving interpretive rigor for quantitative content analysis in

NVivo. A systematic review of theoretical definitions and linguistic patterns informed the refinement process, during which constructs with semantic and empirical convergence were merged. Perceived Ease of Use and Perceived Usefulness were combined to represent functional and experiential efficiency. Attitude toward Use and Behavioral Intention were integrated to reflect a unified behavioral adoption orientation. Perceived Susceptibility and Perceived Severity were likewise consolidated to capture a holistic perception of health vulnerability and risk awareness.

The refinement process resulted in four higher-order analytical themes that guided the NVivo coding structure. Each theme was operationally defined to ensure coding reliability and theoretical clarity, as summarized in Table 2 below.

Table 2. Refined Themes for NVivo Coding

Refined Theme	Merged Constructs	Conceptual Definition
Perceived Ease & Usefulness (PEU)	Perceived Ease of Use Perceived Usefulness	Reflects how users evaluate the device's usability, comfort, and functional benefits for health monitoring.
Attitude & Intention toward Use (ATI)	Attitude toward Use Behavioral Intention	Represents participants' affective responses and their willingness to adopt or recommend the technology.
Health Risk Perception (HRP)	Perceived Susceptibility Perceived Severity	Captures awareness of personal health vulnerability and the perceived seriousness of potential health threats.
Perceived Risk (PR)	Perceived Risk	Encompasses users' concerns about privacy, data security, and trust in algorithmic decision-making.

3.4. Data Analysis

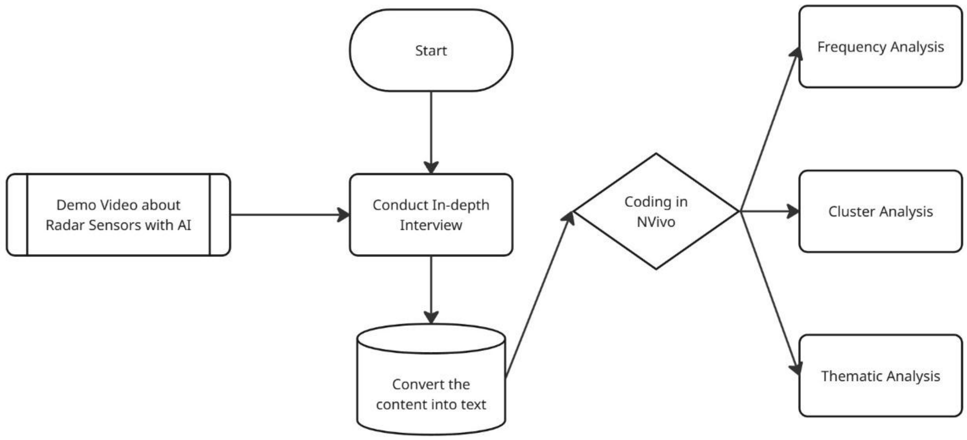

Figure 1. Research Process

The qualitative data were analyzed in NVivo 14 using a structured, theory-driven procedure to convert narrative text into quantifiable evidence. As illustrated in Figure 1, the analytic workflow comprised three integrated stages: frequency analysis, cluster analysis, and thematic analysis, each contributing complementary insights into participants' perceptions of AI-enabled radar health monitoring. Audio recordings were transcribed verbatim and verified for accuracy, then imported into NVivo for quantitative content analysis. Coding followed the refined four-theme structure: Perceived Ease and Usefulness (PEU), Attitude and Intention toward Use (ATI), Health Risk Perception (HRP), and Perceived Risk (PR). Interview transcripts were systematically segmented and coded into these categories to ensure analytical consistency across cases.

The coding process was guided by the conceptual definitions of the four refined themes presented in Table 2. Each paragraph within the interview transcripts was carefully reviewed and coded according to the definition and logical alignment of the corresponding theme. This paragraph-level coding ensured contextual coherence and minimized interpretive ambiguity. Following the principles of quantitative content analysis, coding emphasized the systematic transformation of textual data into measurable thematic categories rather than subjective interpretation. This procedure ensured that the thematic categorization was conceptually valid and replicable, consistent with prior studies employing similar Nvivo-based quantitative content analysis approaches (Ho et al., 2023; Ho et al., 2024).

Second, frequency and cluster analysis was conducted to explore semantic relationships between nodes and terms. NVivo's similarity and hierarchical clustering algorithms were used to visualize interconnections between themes, for example, how "usefulness" co-occurred with "trust" or "health protection." These clusters offered an empirical basis for understanding how participants cognitively associated technological, emotional, and ethical dimensions of AI-based health devices.

Finally, thematic analysis synthesized the coded data into higher-order interpretive patterns. This stage examined how participants framed their attitudes, motivations, and concerns toward AI healthcare technologies. The analysis not only revealed dominant sentiments but also identified underlying conceptual linkages, such as how positive attitudes toward convenience were sometimes tempered by perceived data risks or privacy concerns.

4. Results

4.1. Frequency Analysis

Table 3. Word Frequency (Top 60 Keywords)

#	Word	Freq	#	Word	Freq
1	health	147	31	feature	22
2	device	135	32	idea	22
3	people	91	33	provide	22
4	data	71	34	functions	21
5	think	57	35	elderly	20
6	believe	49	36	accuracy	19
7	demo	40	37	app	19
8	make	38	38	know	19

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9	technology	36	39	looked	19
10	understand	36	40	mobile	19
11	raw	34	41	confusing	18
12	helpful	31	42	consider	18
13	information	31	43	easy	18
14	like	31	44	services	18
15	especially	28	45	use	18
16	heart	28	46	better	17
17	clear	27	47	emergencies	17
18	help	27	48	feel	17
19	monitoring	27	49	found	17
20	using	27	50	good	17
21	results	26	51	important	17
22	trust	26	52	interface	17
23	useful	25	53	watching	17
24	breathing	24	54	analysis	16
25	rate	24	55	explained	16
26	thought	24	56	interesting	16
27	emergency	23	57	time	16
28	medical	23	58	affordable	15
29	something	23	59	alone	15
30	video	23	60	based	15

The frequency analysis was conducted using NVivo to identify the most salient words expressed across participants' interviews regarding their perceptions of AI-integrated radar sensors. The top sixty frequently mentioned terms are presented in Table 3, offering insight into participants' primary areas of emphasis when discussing the device's usability, perceived benefits, and concerns.

As shown in the table, the most dominant keywords were "health" (147), "device" (135), "people" (91), "data" (71), and "think" (57), highlighting that participants primarily focused

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on the health-related value and technological utility of the radar-AI system. Words such as "believe", "helpful", "useful", "clear", and "understand" suggest positive cognitive and affective evaluations, reflecting the construct of Perceived Ease and Usefulness (PEU). These expressions indicate that participants perceived the device as both functionally beneficial and intuitively operable.

Terms including "trust", "accuracy", "results", and "privacy" (although appearing less frequently) align closely with the dimension of Perceived Risk (PR), revealing user concerns about data reliability and the dependability of AI-based interpretations. Meanwhile, recurring words such as "emergency", "help", "monitoring", "medical", and "elderly" correspond to Health Risk Perception (HRP), emphasizing the users' awareness of potential health vulnerabilities and the importance of timely response mechanisms.

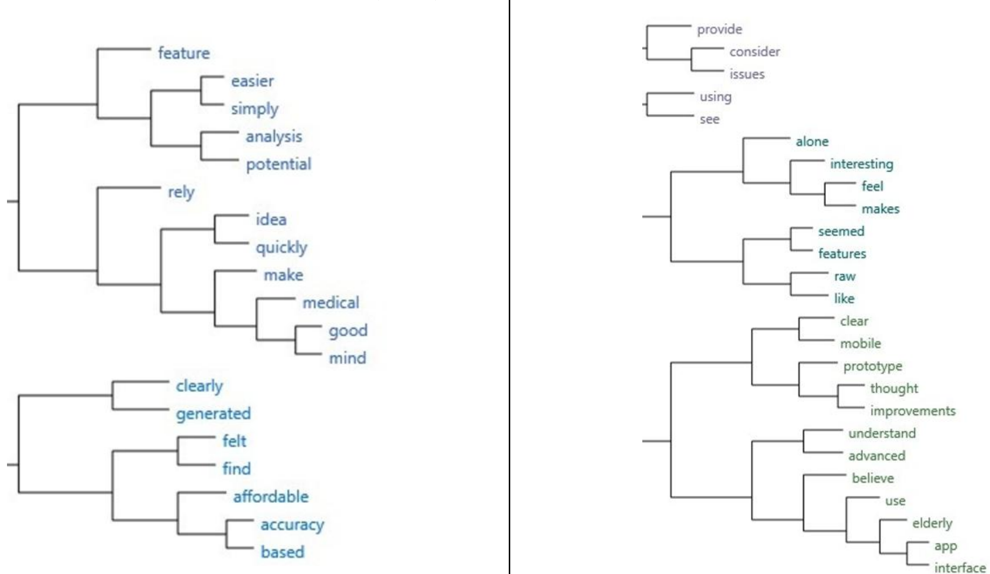
Finally, affective expressions like "interesting", "important", and "good" were frequently co-mentioned with behavioral verbs such as "consider", "use", and "buy", reflecting Attitude and Intention toward Use (ATI). These patterns demonstrate that participants not only evaluated the device positively but also expressed a genuine willingness to adopt it if it were affordable and trustworthy.

Figure 2. Word Cloud

4.2. Cluster Analysis

A cluster analysis in NVivo using Pearson correlation revealed four semantic groupings aligned with the refined TAM–PMT themes: PEU, ATI, HRP, and PR. The first cluster (feature, easier, simply, accuracy, affordable) reflected functional efficiency and confidence in system usability, corresponding to Perceived Ease and Usefulness (PEU). The second cluster captured affective engagement and adoption intent, consistent with Attitude and Intention toward Use (ATI). The third cluster (health, emergencies, monitoring, help, information) denoted concern for preventive care and continuous monitoring, aligning with Health Risk Perception (HRP). The fourth cluster (blood, breathing, reliable, concerns, heart, care, analyze) emphasized trust in physiological measurement accuracy alongside caution regarding data reliability and safety, representing Perceived Risk (PR). These clusters demonstrate coherent linguistic patterns reflecting users' evaluations, emotional responses, and risk considerations toward AI-enabled radar health monitoring.

Perceived Ease and Usefulness (PEU)	Attitude and Intention toward Use (ATI)



Health Risk Perception (HRP)	Perceived Risk (PR)

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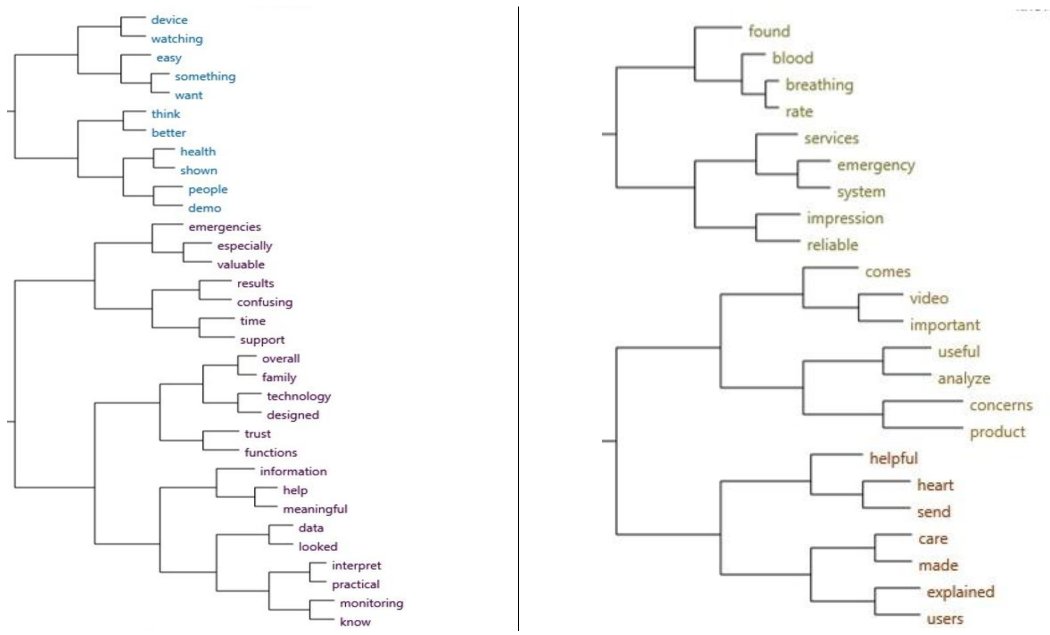

Figure 3. Word cluster analysis of interview data (NVivo output)

4.3. Thematic Analysis

Following the frequency and cluster analyses, a thematic analysis was conducted in NVivo to identify deeper patterns of meaning within participants' narratives. Four overarching themes emerged, reflecting users' cognitive, emotional, and evaluative orientations toward the AI-integrated radar sensor. Table 4 summarizes each theme, its coding frequency, and representative quotes.

The most dominant theme, Perceived Ease and Usefulness (PEU) (226 references), captured participants' views on how effortlessly the device could be used and how effective it was in supporting health monitoring. Participants consistently emphasized the practicality and functional value of AI in interpreting vital signs such as heart rate and breathing patterns. As one respondent explained, "When it comes to using AI to analyze health data such as heart rate and breathing patterns, I think it is very useful" (Participant 1). This reflects confidence in the device's ability to simplify complex information and enhance users' understanding of their own health status.

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This finding illustrates the construct of perceived usefulness and ease of use described in TAM (Davis, 1989), showing that participants cognitively evaluated the technology based on its functional clarity and efficiency.

Table 4. Thematic coding results and representative participant quotes

Code name	Frequency	Example Quote
Perceived Ease and Usefulness (PEU)	226	"When it comes to using AI to analyze health data such as heart rate and breathing patterns, I think it is very useful" (Participant 1)
Perceived Risk (PR)	84	"As for trust, I would say that I would trust the results generated by AI, but I would also be a little cautious" (Participant 11)
Attitude and Intention toward Use (ATI)	74	"If the product were affordable, I would definitely consider using it" (Participant 12)
Health Risk Perception (HRP)	62	"Many elderly people in that situation face difficulties in communicating if something happens, and this sensor would provide a lot of comfort and security for them" (Participant 2)

The second major theme, Perceived Risk (PR) (84 references), revealed users' cautious attitudes toward the reliability of AI-generated health data and concerns regarding data privacy. Many participants expressed conditional trust, acknowledging AI's potential while also recognizing possible inaccuracies. One participant noted, "As for trust, I would say that I would trust the results generated by AI, but I would also be a little cautious" (Participant 11). This theme underscores the need for transparency and accountability in algorithmic decision-making within healthcare technologies. The cautious optimism expressed by participants corresponds to the perceived risk dimension highlighted in prior health technology studies, suggesting that even minor concerns about data accuracy or privacy can shape emotional trust and adoption behavior (Wang et al., 2023)

The third theme, Attitude and Intention toward Use (ATI) (74 references), represented participants' overall emotional responses and behavioral intentions. The interviews revealed a generally positive orientation toward adoption, especially if the product was affordable and perceived as reliable. For example, one respondent stated, "If the product were affordable, I would definitely consider using it" (Participant 12). This indicates that while curiosity and appreciation for innovation drive acceptance, financial accessibility and perceived dependability play crucial moderating roles. This aligns with the behavioral intention component of both TAM and TPB, where a positive attitude and perceived behavioral control jointly influence the intention to adopt innovative technologies (Ajzen, 1991).

Finally, Health Risk Perception (HRP) (62 references) reflected users' motivation to adopt the device as a preventive measure against health vulnerabilities. Participants emphasized the importance of real-time monitoring, particularly for elderly individuals living alone. As Participant 2 noted "Many elderly people in that situation face difficulties in communicating if something happens, and this sensor would provide a lot of comfort and security for them". This theme reveals that perceived susceptibility to health risks acts as a key motivator for technology acceptance in healthcare contexts. This theme reflects the health motivation mechanism central to PMT, where awareness of vulnerability and severity reinforces protective intentions toward adopting supportive technologies (Rogers, 1975).

Table 5. Coding frequency of four main themes across participants

	ATI	HRP	PEU	PR
Participant 1	3	1	14	5
Participant 2	6	2	22	6
Participant 3	7	2	17	5
Participant 4	12	5	12	5
Participant 5	3	3	15	4
Participant 6	3	4	17	5
Participant 7	4	3	16	5
Participant 8	4	5	17	5

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Participant 9	4	5	18	5
Participant 10	4	5	12	6
Participant 11	4	6	13	6
Participant 12	6	5	12	7
Participant 13	5	5	13	7
Participant 14	4	6	13	7
Participant 15	5	5	15	6

Note. Perceived Ease and Usefulness (PEU), Attitude and Intention toward Use (ATI), Health Risk Perception (HRP), and Perceived Risk (PR)

Table 5 presents the distribution of the four major themes, Perceived Ease and Usefulness (PEU), Attitude and Intention toward Use (ATI), Health Risk Perception (HRP), and Perceived Risk (PR), across the fifteen interview participants. Among these, PEU appeared most frequently, with an average of over 15 coded references per participant, indicating that participants placed strong emphasis on the device's functional benefits and user-friendliness. Many participants consistently described the radar-AI device as "easy to use", "helpful", and "practical", highlighting their appreciation of its ability to simplify complex health information. This prevalence suggests that perceived usefulness and ease of operation are the most salient factors influencing positive attitudes toward adoption.

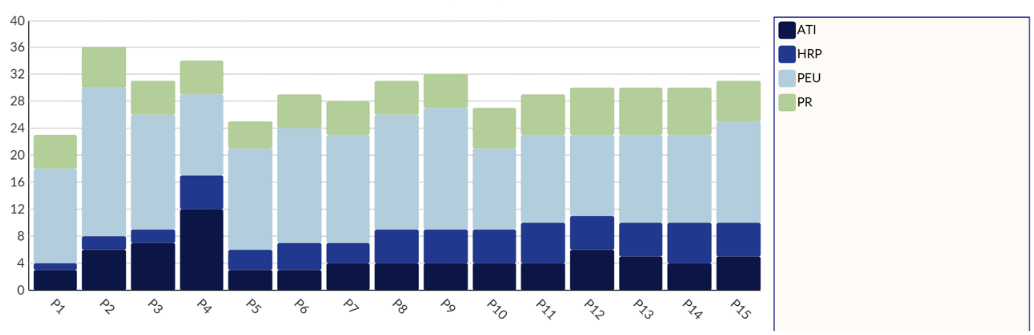

Figure 4. Coding frequency of four main themes across participants

In contrast, the frequencies of ATI, HRP, and PR were relatively moderate yet consistent, reflecting complementary aspects of participants' overall perception. ATI codes reflected curiosity, favorable evaluation, and willingness to adopt, particularly when affordability and reliability were emphasized. HRP codes revealed participants' awareness of health vulnerability, especially among the elderly, suggesting that risk perception motivates adoption as a preventive measure. Meanwhile, PR codes captured cautious attitudes toward AI accuracy and data privacy, showing that while users were optimistic, they remained mindful of technological limitations. Collectively, the frequency pattern demonstrates a balanced and realistic evaluation of the device, in which cognitive benefits (PEU), motivational factors (ATI and HRP), and cautious awareness (PR) jointly shape behavioral intention within the extended TAM–PMT framework.

5. Conclusion

5.1. Discussion

The findings from the NVivo-based analysis revealed that Perceived Ease and Usefulness (PEU) was the most dominant theme across participants, indicating that users primarily evaluated the AI health-monitoring device through its functional efficiency and simplicity. This aligns with the central propositions of the Technology Acceptance Model (TAM), where perceived usefulness and ease of use significantly predict users' attitudes toward adopting new technologies (Davis, 1989). Participants frequently described the device as "helpful", "clear", and "practical", reflecting their confidence in its potential to simplify health tracking and enhance daily life convenience. These results reinforce prior research emphasizing that perceived ease of operation is a critical factor driving acceptance of digital health tools (Liu et al., 2023). Unlike traditional survey-based studies, this research captures the spontaneous expressions that users associate with efficiency and clarity, offering a richer understanding of how usability translates into positive attitudes toward AI-enabled healthcare technologies.

The moderate but consistent appearance of Attitude and Intention toward Use (ATI) and Health Risk Perception (HRP) further highlights that acceptance of AI-driven health technologies are not only shaped by usability but also by emotional and health-related motivations. Many participants expressed a willingness to adopt the device for themselves or their family members, particularly elderly relatives living alone. This reflects a preventive orientation toward health, consistent with the Protection Motivation Theory (PMT), which posits that perceived vulnerability and severity of health threats encourage protective behaviors (González-Castro et al., 2021). By combining TAM, PMT, and TPB perspectives, this study advances current understanding by showing that behavioral intention toward AI technologies is simultaneously motivated by perceived usability and perceived health vulnerability, reinforcing the multidimensional nature of technology acceptance in healthcare contexts.

Lastly, the emergence of Perceived Risk (PR) as a recurring but less dominant theme indicates that users were cautiously optimistic about AI reliability and data privacy (Gerlich, 2023). Although some participants expressed concerns about the accuracy and safety of personal data, these worries did not translate into rejection or distrust. Instead, users demonstrated a balanced stance, trusting AI's capabilities while remaining aware of its limitations (Polemi et al., 2024). The present study contributes further by illustrating this balance linguistically through participants' cautious but accepting tone. Such results provide nuanced insight into how users cognitively negotiate trust and skepticism, expanding prior models of AI acceptance that often treat these constructs as dichotomous.

5.1. Implications

This study contributes to the growing body of literature on technology acceptance in healthcare by extending the TAM–PMT integrated framework and validating it through quantitative NVivo-based content analysis. The results demonstrate that perceived usefulness and ease of use remain the most salient predictors of positive user evaluation, supporting the core logic of TAM (Davis, 1989). However, the integration of health-related motivational constructs, perceived susceptibility and severity, provides additional explanatory power, emphasizing that technology acceptance in healthcare is not solely a cognitive process but also involves emotional and preventive motivations. This approach strengthens the multidimensional understanding of how users cognitively and affectively evaluate AI-based healthcare innovations.

From a managerial perspective, the findings highlight several practical directions for designers and developers of AI-driven health monitoring systems. First, usability and clarity of information should remain the top priority, as users consistently emphasized convenience, ease of operation, and understandable data visualization as key factors driving adoption. Second, trust-building mechanisms, such as transparent data usage policies, accuracy validation, and privacy safeguards, must be integrated into both device design and marketing communication to alleviate perceived risk. Third, the study underscores the importance of tailoring user interfaces to different demographic groups, especially older adults, who may require simplified navigation and voice-assisted functions.

5.2. Limitations and Future Research

Although this study offers meaningful insight into user perceptions of AI-enabled radar health monitoring, several limitations must be noted. The sample size was small and based on qualitative data, which constrains generalizability despite the use of NVivo to quantify linguistic patterns. Perceptions were elicited through a demo video rather than real-world usage, which may limit ecological validity and the accuracy of emotional or behavioral inferences. The analysis focused on four integrated constructs (Perceived Ease and Usefulness, Attitude and Intention toward Use, Health Risk Perception, and Perceived Risk), which may omit other salient psychosocial or contextual determinants such as technological anxiety, cultural norms, or ethical concerns.

Future work should enhance external validity through mixed-method designs, including large-scale surveys or experiments to empirically test causal pathways in the extended TAM–PMT model. Longitudinal studies could capture evolving perceptions during sustained system interaction and trust formation. Cross-cultural comparative research may clarify how cultural backgrounds shape privacy sensitivity and health-related motivation. Additionally, incorporating emerging constructs such as explainability, algorithmic transparency, and human–AI trust calibration would strengthen theoretical coverage of ethical and socio-technical dynamics in AI-mediated healthcare adoption.

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