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Reassuring Invisibility: Designing AI Health Platforms for Intergenerational Caregiving

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Abstract

Background Invisible artificial intelligence (AI) health platforms are increasingly proposed as unobtrusive infrastructure for supporting aging populations within family care environments. However, systems designed to operate in the background also introduce tensions related to trust, surveillance, autonomy, and interpretability. Most existing research has examined individual technology adoption and older-adult usability, with comparatively less attention to how invisible AI is anticipated and evaluated within intergenerational caregiving relationships before deployment.

Methods This study employed an explanatory sequential mixed-methods design. A quantitative survey of baby boomers and adult children (N = 375) examined relationships among anticipated usability, eHealth literacy, and perceived wellbeing in relation to a proposed invisible AI health platform. Participatory design interviews with adult children (N = 16) subsequently explored how participants interpreted, constrained, and redesigned the platform within everyday caregiving contexts. Qualitative data were analyzed using Saldaña's two-cycle coding approach, with inter-coder agreement assessed using Cohen's kappa.

Results Anticipated usability was strongly associated with perceived wellbeing, and the estimated indirect effect of eHealth literacy on perceived wellbeing through anticipated usability was statistically significant. The direction and significance of these results remained after three semantically proximate items were excluded, although discriminant validity between anticipated usability and perceived wellbeing was not supported. Changes in model-fit indices supported metric and scalar invariance across the two groups despite marginal configural fit, providing qualified support for pooled analysis. Selected differences in construct means and in the anticipated usability–perceived wellbeing path remained. Qualitative analysis produced four themes, which were developed through integration into four proposed conditions of acceptability: relational fit, bounded and verifiable trust, dignity preservation, and coordination over intervention.

Conclusions The study develops reassuring invisibility as a conditional relational state in which the potential inspection deficit created by background operation is counterbalanced by relational, epistemic, and governance conditions. Within this framework, invisibility is treated not solely as a technical property but as a relationally achieved state. The concept extends calm technology, ambient intelligence, and privacy-by-design by proposing an account of the conditions under which unobtrusive AI may become supportive rather than opaque, intrusive, or unaccountable. These conditions require further testing with deployed systems and direct participation by older adults.

Keywords Invisible AI, Reassuring Invisibility, Family Care, AI Health Platform, Participatory Design, Calm Technology

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1. Introduction

By 2030, one in six people worldwide will be aged 60 years or over (World Health Organization [WHO], 2025). As populations age, much of the everyday support required by older adults continues to be provided by family members and other informal caregivers, although the extent of this reliance varies across countries and care systems (Lindeman et al., 2020; Rocard & Llena-Nozal, 2022). Many older adults prefer to remain in familiar homes and communities while retaining choice, independence, autonomy, and meaningful relationships (Wiles et al., 2012). At the same time, family members frequently contribute to care coordination, monitor changes in health or routine, and connect care recipients with information, services, and healthcare professionals (Lindeman et al., 2020). These arrangements can create tension between an older adult's desire for autonomy and a caregiver's need for sufficient information to provide timely support.

Recent developments in digital health have expanded the range of AI-mediated systems proposed for supporting aging in place and family caregiving. These developments draw on calm technology, which considers how computing may move between the center and periphery of attention (Case, 2015; Weiser, 1991; Weiser & Brown, 1996), ambient intelligence, which envisions context-aware computational capabilities embedded within everyday environments (Aarts & Wichert, 2009), and privacy-by-design, which seeks to embed privacy protections into system architecture and operation (Cavoukian et al., 2010; Langheinrich, 2001). Assisted-living and remote-care systems increasingly incorporate connected sensors, ambient monitoring, automated analysis, and platform-based coordination to support safety and care without requiring continuous direct interaction (Lindeman et al., 2020; Sapci & Sapci, 2019). Their appeal lies in the possibility of providing support that remains available without becoming continuously demanding. However, reduced visibility can also make sensing, inference, information sharing, and automated intervention more difficult to inspect, evaluate, or contest.

Research on aging-in-place technologies has identified numerous factors affecting acceptance before and after implementation, including perceived usefulness, usability, privacy, need, available alternatives, and social influence (Peek et al., 2014). Nevertheless, existing work offers more limited guidance on how a background AI health platform is evaluated before deployment when the relevant judgment is distributed across an older adult, adult children, and potentially health professionals. This problem has three connected facets. Temporally, initial evaluation necessarily precedes use, while background operation may subsequently provide fewer opportunities for direct inspection than a conventional interactive system. Relationally, technology decisions in family care may involve people who evaluate, introduce, configure or coordinate a system with or on behalf of an older adult (Lindeman et al., 2020). Gerontechnology research has also shown that design practices do not merely respond to older users but actively configure assumptions about older age, capability, dependency and participation (Bischof & Jarke, 2021). Conceptually, calm technology, ambient intelligence, and privacy-by-design provide important guidance concerning peripheral interaction, contextual responsiveness, and privacy protection, but provide less explicit guidance on how

relational fit, epistemic assurance, dignity, and proportionality should jointly govern invisible AI in family care.

The present study addresses these facets through an explanatory sequential mixed-methods design. RQ1 examines how anticipated usability and eHealth literacy are associated with perceived wellbeing before deployment. RQ2 examines how adult children interpret, constrain, and redesign a proposed invisible AI health platform in relation to caregiving practices. RQ3 integrates the quantitative and qualitative findings to develop candidate conditions under which background operation may become acceptably unobtrusive. The study combines a quantitative survey of baby boomers and adult children (N = 375) with participatory design interviews involving adult children (N = 16). Figure 1 represents the proposed platform as a background coordination layer situated across family activities, communication practices, and distributed health-support arrangements rather than as a standalone technology.

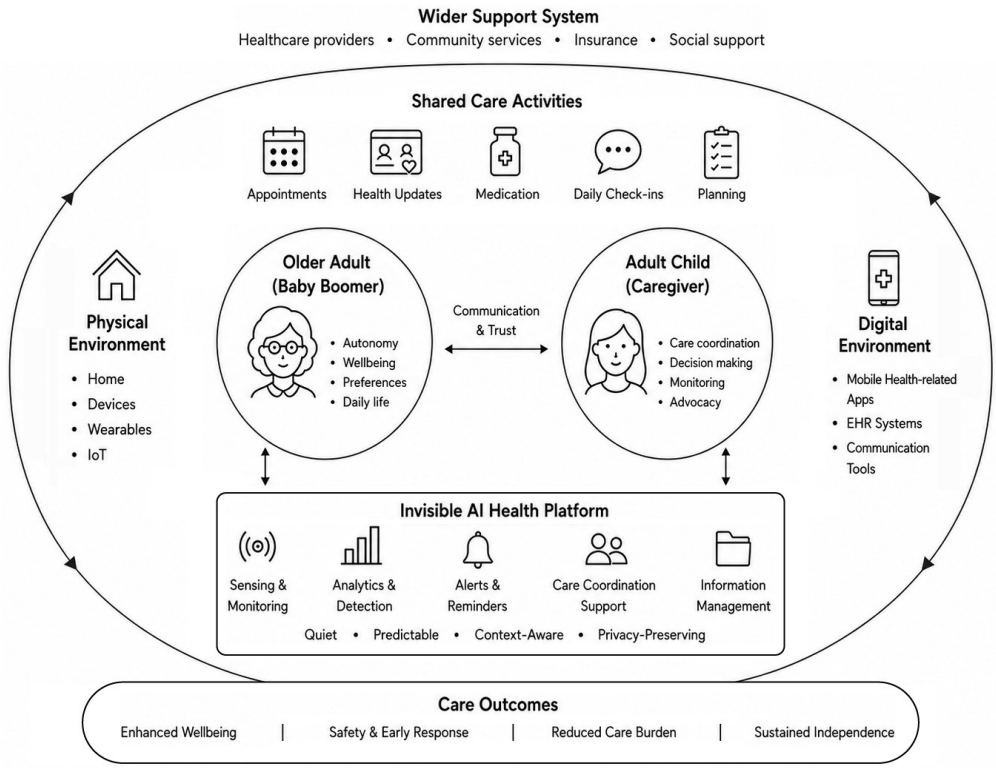


Figure 1 Intergenerational Caregiving Ecosystem with Invisible AI Health Platform

To address the conceptual problem, the study develops reassuring invisibility as a conditional relational state in which a system can remain peripheral to attention because those affected retain credible grounds to evaluate, contest, and govern its consequential behavior. The concept treats acceptable invisibility not solely as a technical property but as an evaluative outcome shaped by relational fit, verifiable trust, dignity-preserving governance, and proportionate intervention. These conditions are developed through integration of the study

findings and are presented as propositions requiring further comparative, longitudinal, and experimental testing. Section 2 presents the theoretical framework and research questions. The term invisible artificial intelligence (AI) health platform is used as the primary descriptor throughout the manuscript; the shortened terms invisible AI, system, and platform are used where the intended meaning is clear.

2. Literature Review

2. 1. Invisible AI Platform in Intergenerational Caregiving

In this study, invisible AI health platform is used as a working term for an AI-mediated system that can perform routine sensing, analysis, monitoring or coordination in the background without requiring sustained user attention. Such a system is not assumed to be continuously imperceptible or entirely interaction-free. Instead, routine functions may remain peripheral while consequential actions such as information sharing, scheduling, escalation, or changes in access require visible explanation, confirmation or control. This definition draws on ubiquitous and calm computing, ambient intelligence, and research on AI-supported and remotely monitored care environments (Aarts & Wichert, 2009; Sapci & Sapci, 2019; Weiser, 1991; Weiser & Brown, 1996).

In eldercare contexts, relevant technologies include connected fall-detection systems, medication and appointment support, physiological monitoring, symptom-related decision support, and digital communication or coordination tools for older adults and caregivers (Karimian et al., 2022; Lindeman et al., 2020; Sapci & Sapci, 2019). These functions differ in their visibility and level of autonomy. Some operate through passive or ambient sensing, while others require conversation, configuration, confirmation or review. Their common objective is not to eliminate interaction but to reduce unnecessary cognitive and behavioral demands by embedding routine support within everyday activities.

This direction is particularly relevant to intergenerational caregiving, in which older adults and family caregivers may negotiate competing needs for autonomy, reassurance, safety and access to information. Research on aging in place indicates that many older adults value independence, choice, continuity of place, and meaningful relationships (Wiles et al., 2012). Family caregivers may contribute to monitoring, health-information exchange, service coordination, and communication with healthcare professionals, including through digital platforms and connected technologies (Lindeman et al., 2020; Quinn et al., 2019). Background systems may assist these arrangements, but their acceptability cannot be inferred from functional convenience alone.

The ambient operation of these technologies introduces corresponding ethical and epistemic tensions. Systems that reduce interruption may also make sensing, inference, information sharing and automated recommendations more difficult to notice, interpret, or question. Research on algorithmic systems and ambient intelligence in healthcare has identified concerns involving surveillance, privacy, informed consent, opacity, autonomy, fairness, and

overreliance on automated outputs (Crawford & Calo, 2016; Karimian et al., 2022; Mittelstadt et al., 2016). These concerns may become especially complex when older adults, family members and health professionals have different informational needs and unequal authority over system deployment and use.

Research on older-adult technology acceptance has examined perceived usefulness, usability, privacy, social influence, cost, need, and alternatives to technology before and after implementation (Chen & Chan, 2014; Peek et al., 2014; Vaportzis et al., 2017). However, this literature provides comparatively limited guidance on how background AI is evaluated across family relationships or how responsibilities for consent, interpretation, configuration, and intervention should be distributed within intergenerational care. This study addresses the gap by examining both prospective evaluations of a proposed platform and the relational and ethical boundaries articulated by adult children.

2. 2. Theoretical Framework

This study draws on three complementary theoretical traditions: calm technology, ambient intelligence, and privacy-by-design. Calm technology, developed from ubiquitous-computing research, considers how information technologies may move between the center and periphery of human attention (Weiser, 1991; Weiser & Brown, 1996). Rather than demanding continuous interaction, a calm system should communicate in ways proportionate to the user's current needs and draw focused attention when circumstances require it. Later design work elaborated principles for reducing unnecessary interruption in increasingly networked environments (Case, 2015). These ideas provide an attentional perspective for systems intended to perform routine functions in the background.

Ambient intelligence concerns computational capabilities embedded within everyday environments that sense context and respond to users or changing circumstances (Aarts & Wichert, 2009). In healthcare and aging research, this tradition has informed smart-home technologies, connected sensors, assisted-living systems, and remote monitoring intended to support safety and independent living (Sapci & Sapci, 2019; Sixsmith & Gutman, 2013). Ambient responsiveness can reduce the need for repeated direct input, but it also raises questions about the validity of system inferences, the visibility of sensing, and the appropriateness of automated responses.

Privacy-by-design argues that privacy should be incorporated proactively into system architecture, default settings, data practices, and governance rather than added after deployment (Cavoukian et al., 2010; Langheinrich, 2001). This approach is especially relevant to background health systems because their operation can involve persistent data collection, sensitive inferences, multiple information recipients, and limited awareness of when processing occurs. Privacy-by-design provides safeguards for these information practices, although privacy protection alone does not determine whether a system is clinically credible, relationally appropriate, or proportionate to a caregiving need.

Together, these traditions clarify important dimensions of invisible AI. Calm technology addresses attentional positioning, ambient intelligence addresses context-aware sensing

and responsiveness, and privacy-by-design addresses proactive information protection and governance. These traditions overlap and are broader than these simplified distinctions, but none alone fully explains how background AI is anticipated and evaluated across intergenerational caregiving relationships. The present study builds on them by examining how attentional, technical, informational, and relational considerations interact in judgments of usability, trust, dignity and family coordination.

2. 3. Analytical Framework

The empirical analysis integrates three respondent-level constructs: anticipated usability, eHealth literacy, and perceived wellbeing. Together, these constructs provide a framework for examining how respondents evaluate a proposed invisible AI health platform before deployment. Because the platform had not been deployed, the constructs were assessed through self-reported judgments made in relation to the proposed system. Table 1 summarizes the conceptual basis, dimensions, item identifiers and representative survey items used to measure each construct.

Table 1 Quantitative Measurement Items by Construct

Construct / Instrument	Dimension	ID	Sample Survey Item
Anticipated Usability ISO 9241–11 (ISO, 2018)	Effectiveness	UE	It would give me helpful reminders when I need them.
	Efficiency	UF	It would make managing my health easier and less stressful.
	Satisfaction	US	I would feel comfortable using this platform in daily life.
eHealth Literacy eHEALS (Norman & Skinner, 2006)	Navigation	LN	I know where to find useful health resources on the Internet.
	Evaluation	LE	I can tell whether online health information is reliable or not.
	Application	LA	I know how to use health information I find online.
Perceived Wellbeing PERMA–Profiler (Butler & Kern, 2016; Seligman, 2011)	Positive Emotion	WP	I would feel more relaxed and positive about managing my health.
	Engagement	WE	My daily routines would feel smoother and easier to manage.
	Relationships	WR	I would feel more connected and supported.
	Meaning	WM	I would feel that taking care of family health is meaningful.
	Accomplishment	WA	I would reach my daily health goals more easily.

2. 3. 1. Anticipated Usability

ISO 9241-11 defines usability as the extent to which specified users can achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use (International Organization for Standardization [ISO], 2018). The standard treats usability as an outcome of use. Because participants in the present study evaluated a proposed platform rather than an operational system, these three dimensions were adapted prospectively. Anticipated usability therefore refers to respondents' expectations that the platform would provide effective support, make health-management activities easier, and feel satisfactory or comfortable in everyday life. It does not represent observed task performance or post-use usability.

Technology-adoption research distinguishes expectations formed before adoption from confirmation and continuance judgments formed through experience (Bhattacherjee, 2001; Venkatesh & Bala, 2008). Studies comparing evaluation before and after system use similarly indicate that prospective expectations and experienced usability are not necessarily equivalent. Anticipated usability is therefore relevant to initial adoption decisions, particularly because age-related changes and differences in technology experience may

shape older adults' expectations and perceived barriers. Subsequent experience may confirm, revise, or contradict these initial expectations (Charness & Boot, 2009; Lee & Koubek, 2010).

Anticipated usability is especially relevant to invisible AI because potential users and family members must initially evaluate whether background sensing, information sharing, recommendations, and intervention rules appear understandable, manageable, and compatible with everyday care. Initial judgments are necessarily prospective, but continued acceptance would also require opportunities for notice, explanation, review, modification, and withdrawal as users acquire experience with the system.

2. 3. 2. eHealth Literacy

eHealth literacy refers to the ability to seek, find, understand, evaluate and apply health information obtained through electronic sources (Norman & Skinner, 2006). The eHealth Literacy Scale, or eHEALS, was developed to assess respondents' perceived knowledge, comfort, and skills in finding, evaluating, and applying electronic health information. In the present study, items adapted from eHEALS were organized into navigation, evaluation, and application dimensions, as shown in Table 1. The resulting scores represent self-reported eHealth literacy rather than objectively demonstrated digital competence.

In family care, relevant health knowledge and digital capabilities may be distributed across several people. An older adult may contribute experiential knowledge of symptoms, routines, and preferences, while an adult child may assist with information searching, platform configuration, and interpretation. This distributed perspective is theoretically relevant to intergenerational caregiving, although the quantitative survey measures respondents individually rather than assessing shared or dyadic literacy. The relational distribution of knowledge and technological responsibility is examined further in the qualitative phase.

2. 3. 3. Perceived Wellbeing

Perceived wellbeing is conceptualized through the PERMA framework, encompassing positive emotion, engagement, relationships, meaning, and accomplishment (Seligman, 2011). The PERMA-Profiler was developed to assess these five psychological dimensions of flourishing (Butler & Kern, 2016). As summarized in Table 1, the present study adapted these dimensions to the proposed-platform context through items asking respondents how they believe the system would affect their feelings, daily routines, relationships, sense of meaning, and health-related goal attainment.

The construct is retained as perceived wellbeing because it captures respondents' perceptions across the five PERMA domains. However, the items are prospectively phrased and platform-referent; consequently, the scores represent perceived wellbeing in relation to the proposed system rather than respondents' current general wellbeing or an observed change following use. The cross-sectional pre-deployment design therefore cannot establish that using the platform improves wellbeing.

The PERMA framework is relevant to aging and family care since wellbeing in later life is associated with social connectedness, autonomy, purpose, and meaningful activity as well as physical health (Ryff, 2014; Steptoe et al., 2015). A platform perceived as reducing

coordination burden or supporting family communication may be evaluated positively across these domains, whereas one perceived as intrusive, demanding or surveillant may be evaluated less favorably. Nevertheless, the substantial empirical overlap found between anticipated usability and perceived wellbeing limits claims that the two measures represent fully distinct constructs. Their relationship is therefore interpreted as an association between closely related prospective evaluations rather than as a distinct causal effect of usability on wellbeing.

Combined, anticipated usability, eHealth literacy, and perceived wellbeing provide an analytical framework for examining prospective evaluations of invisible AI health platforms. Anticipated usability captures expected manageability and functional value; eHealth literacy captures perceived ability to locate, evaluate, and apply electronic health information; and perceived wellbeing captures anticipated perceptions across the five PERMA domains. The qualitative phase extends this respondent-level analysis by examining the family relationships, ethical boundaries, and governance expectations within which these evaluations are formed.

Accordingly, the temporal, relational, and conceptual facets of the research problem generate the following research questions:

RQ1. How are anticipated usability and eHealth literacy associated with perceived wellbeing in relation to a proposed invisible AI health platform among baby boomers and adult children?

RQ2. How do adult children participate in evaluating and refining a proposed invisible AI health platform within intergenerational caregiving contexts, and what relational and ethical tensions emerge through this process?

RQ3. What conditions contribute to the acceptability of invisible AI health platforms, and how do these conditions inform design and governance implications for HCI and digital health?

3. Methods

3. 1. Research Design

This study employed an explanatory sequential mixed-methods design structured around three research questions (Creswell & Plano Clark, 2018). The study proceeded through two connected phases. First, a quantitative survey examined relationships among anticipated usability, eHealth literacy, and perceived wellbeing among baby boomers and adult children evaluating a proposed invisible AI health platform (RQ1). Second, scenario-based participatory design interviews with adult children examined how participants interpreted, evaluated, constrained, and refined the proposed platform within caregiving contexts (RQ2). Integration of the quantitative and qualitative findings informed the analysis of conditions

shaping platform acceptability and corresponding design and governance implications (RQ3). The qualitative phase was used to interpret and contextualize patterns identified in the quantitative phase, particularly the social meaning of anticipated usability, the role of eHealth literacy in prospective platform evaluation, and the relational and ethical boundaries that were not captured by the respondent-level survey measures. Integration occurred primarily during interpretation and is reported in Section 5.1.

3. 2. Quantitative Phase

3. 2. 1. Participants and Recruitment

Survey data were collected from 375 respondents. For the role-based analysis, respondents aged 60–79 were classified as baby boomers (N = 226), while respondents aged 20–59 were classified as adult children (N = 149). Because the analytical dataset did not contain a separate role variable, these classifications were operationalized using age. They should not be interpreted as verified parent-child dyads. The age bands are an approximate operationalization and do not correspond exactly to birth cohorts; respondents at the lower boundary of the older group may fall outside the conventional baby boomer definition.

Participants were recruited through SurveyCircle and purposive outreach using social media and caregiving-related community networks. The sample was intended to capture prospective evaluations from older adults who could become care recipients and younger adults who could participate in family caregiving or technology-related coordination. The data were collected across geographically distributed respondents, but geographic and cultural variation was not incorporated into the analytical models.

Table 2 Survey Participant Characteristics by Age–Operationalized Group (N = 375)

Characteristics	Category	Total (%)	AC (%)	BB (%)
Group	Adult child (AC)	149 (39.7)	149 (100.0)	0
	Baby boomer (BB)	226 (60.3)	0	226 (100.0)
Age	20~29	6 (1.6)	6 (4.0)	0
	30~39	48 (12.8)	48 (32.2)	0
	40~49	52 (13.9)	52 (34.9)	0
	50~59	43 (11.5)	43 (28.9)	0
	60~69	186 (49.6)	0	186 (82.3)
	70~79	40 (10.7)	0	40 (17.7)
Gender	Woman	201 (53.6)	76 (51.0)	125 (55.3)
	Man	170 (45.3)	69 (46.3)	101 (44.7)
	Non-binary	2 (0.5)	2 (1.3)	0
	Prefer not to say	2 (0.5)	2 (1.3)	0
Region	Asia	186 (49.6)	104 (69.8)	82 (36.3)
	Europe	109 (29.1)	30 (20.1)	79 (35.0)
	North America	59 (15.7)	9 (6.0)	50 (22.1)
	Africa	15 (4.0)	2 (1.3)	13 (5.8)
	South America	6 (1.6)	4 (2.7)	2 (0.9)
Anticipated Usability	Mean (SD)	3.72 (0.93)	3.74 (0.76)	3.71 (1.04)
eHealth Literacy	Mean (SD)	3.77 (0.86)	3.57 (0.87)	3.90 (0.83)
Perceived Wellbeing	Mean (SD)	3.52 (1.06)	3.65 (0.85)	3.43 (1.17)

Note: Groups were defined by age and were not verified caregiving roles. Total percentages may not sum to 100% due to rounding.

3. 2. 2. Platform Description and Measures

Before completing the survey, participants reviewed a description of the proposed invisible AI health platform. The concept included passive or low-interaction monitoring, conversational health check-ins, AI-assisted reminders, health-management support, and family-care coordination. Participants evaluated a proposed system rather than a deployed platform or functional prototype.

The survey contained 26 construct items rated on a five-point response scale. The items were adapted from three conceptual or measurement sources. Anticipated usability was measured with eight items across effectiveness (UE1–UE3), efficiency (UF1–UF3), and satisfaction (US1–US2). eHealth literacy was measured with eight items across navigation (LN1–LN3), evaluation (LE1–LE3), and application (LA1–LA2). Perceived wellbeing was measured with ten platform-referent items across positive emotion (WP1–WP2), engagement (WE1–WE2), relationships (WR1–WR2), meaning (WM1–WM2), and accomplishment (WA1–WA2). Because the items were adapted and prospectively worded, the survey did not administer ISO 9241-11, eHEALS, or the PERMA-Profiler as unchanged standardized instruments. As shown in Table 1, prospective wording such as “it would” and “I would” was used because participants evaluated the platform before deployment, consistent with research distinguishing pre-use expectations from evaluations formed after experience (Lee & Koubek, 2010).

3. 2. 3. Quantitative Analysis

Internal consistency and factor suitability were assessed using Cronbach’s alpha, Kaiser–Meyer–Olkin sampling adequacy, and Bartlett’s test of sphericity. Exploratory factor analysis with varimax rotation examined the item structure of anticipated usability, eHealth literacy, and perceived wellbeing. Zero-order correlations examined bivariate relationships among composite scores.

Regression analyses examined associations among eHealth literacy, anticipated usability and perceived wellbeing. PROCESS Model 4 estimated the indirect effect of eHealth literacy on perceived wellbeing through anticipated usability using 5,000 bootstrap samples and percentile-based 95% confidence intervals. Because the data were cross-sectional, the indirect effect was not interpreted as temporal or causal mediation. PROCESS Model 1 tested whether eHealth literacy moderated the anticipated usability–perceived wellbeing association. Variance inflation factors and the Durbin–Watson statistic were used as diagnostics of multicollinearity and first-order residual autocorrelation, respectively. PROCESS Models 4 and 1 were specified following Hayes (2022).

Given semantic proximity between anticipated usability and perceived wellbeing items, discriminant validity was assessed using the composite-score correlation, heterotrait–monotrait (HTMT) ratio, average variance extracted (AVE), Fornell-Larcker comparison, and normal-theory maximum-likelihood CFA comparing one- and two-factor models. Five-point items were treated as continuous. Harman’s unrotated first component was examined only as a limited common-method-variance (CMV) diagnostic. These analyses are reported in Table 9.

Sensitivity analysis repeated the standardized regression and indirect-effect analysis after excluding UF2, WE2, and WA2, using 10,000 nonparametric bootstrap samples (Table 10). Role-based analyses compared the age-operationalized groups using Welch t-tests, permutation-based Hotelling $T2$, and multigroup CFA of configural, metric, and scalar invariance. Group-specific standardized path estimates were compared using 10,000 bootstrap samples (Table 12).

The pooled model remained the primary analysis because changes in fit indices provided qualified support for metric and scalar invariance. However, pooled estimates were interpreted alongside role-specific results given marginal configural fit and selected group differences.

3. 3. Qualitative Phase

3. 3. 1. Participants and Recruitment

The qualitative phase included 16 adult children of baby boomers (P1–P16). Participants were purposively recruited to obtain variation in caregiving intensity, parental digital readiness, geographic context, and professional background. Adult children were selected because family members may participate in evaluating, introducing, configuring, or coordinating technologies intended to support an older adult (Lindeman et al., 2020; Quinn et al., 2019). The study did not treat the adult children as substitutes for older-adult participation. Instead, they were examined as one stakeholder group whose evaluations could influence family-level technology decisions. Participant characteristics, care context, and principal participatory-design contributions are summarized in Table 3.

Table 3 Interview Participant Characteristics and Design Contributions (N = 16)

ID	Profession	Care Context	Care Intensity	Digital Readiness	Participatory–Design Contribution
P1	ENT doctor	Co–residing with healthy parents	●●○○○	●●●○○	Clinically grounded information and protection from misinformation or commercial bias
P2	Accounting assistant	Parent living alone with stable daily routines	●●●○○	●○○○○	Sustainable health management through simple daily routines and reminders
P3	Private educator	Co–residing parents with stable lifestyles	●●○○○	●●○○○	Preference for simplicity and reduced feature complexity
P4	CPA	Parents managing chronic conditions	●●●○○	●●●●○	One–click accessibility and low–burden interaction
P5	Wellness coach	Parents managing diabetes and hypertension	●●●●●	●●●○○	Emotional reassurance without replacing human caregiving relationships
P6	Textile designer	Socially active and independent parents	●●●●○	●●●●●	AI as a practical support layer rather than a substitute for care
P7	Lawyer	Indirect caregiving through family communication	●●●○○	●●○○○	Privacy protection, dignity preservation, and anti–surveillance boundaries
P8	Homemaker	Multi–generational household with aging but active parents	●●●●●	●●●●○	Inclusive access and emotional reassurance across family members
P9	Orthopedist	Parents living independently with stable routines	●●●○○	●●●○○	Pragmatic health monitoring and clinically interpretable support

P10	Financial consultant	Parents living separately with limited emotional disclosure	●●○○○	●○○○○	AI as a mediated channel for sensitive health communication
P11	Healthcare administrator	Independent, working parents	●●●○○	●●○○○	Light–touch monitoring and bidirectional family reminders
P12	Creative director	Co–residing parents supported by extended family	●●●●●	●○○○○	Family coordination and trust contingent on system reliability
P13	Startup CEO	Independent parents in long–distance caregiving context	●●●○○	●●○○○	Accuracy, misinformation prevention, and distance–care coordination
P14	Executive producer	Shared caregiving across multilingual family members	●●○○○	●●○○○	Multilingual accessibility and culturally inclusive interaction
P15	Marketing manager	Independent, self–managing parents	●●○○○	●●●○○	Intuitive interaction and accessibility for aging users
P16	Design professional	Independent, self–managing parents	●○○○○	●●●●○	Diversity of aging users' experiences and child–centered care perspectives

Note: Care intensity reflects participants' reported level of emotional, practical and digital involvement in parental health management. Digital readiness reflects participants' reports of their parents' comfort and familiarity with smartphones, health applications and related digital technologies. (●○○○○ = low; ●●●●● = high)

3. 3. 2. Scenario Development and Interview Protocol

All participants reviewed a digital informed-consent form and indicated agreement before participation. Under the institution's low-risk research guidelines, the study was deemed exempt from IRB review.

Scenario-based participatory design interviews elicited expectations, concerns, and design judgments regarding an invisible AI health platform not yet deployed in practice (Bødker, 2000; Carroll, 2000). Illustrated design probes made the unfamiliar platform concept more tangible and supported critical and imaginative responses (Gaver et al., 1999; Mattelmäki, 2006). Informed by calm technology principles, the scenarios varied the extent to which interaction, processing, and information sharing remained in the background (Case, 2015; Weiser & Brown, 1996).

The sessions are characterized as participatory design rather than co-design. Participants proposed revisions, articulated boundaries, and reframed platform features, but participated through a single interview using researcher-developed scenarios rather than an iterative design partnership. This reflects scholarship treating participation as variable by phase, role, and degree of involvement (Halskov & Hansen, 2015; Sanders & Stappers, 2008; Steen, 2013).

Scenario development proceeded in three stages. First, a preliminary review identified caregiving domains including medication support, appointment coordination, fall detection, psychological monitoring, and caregiver situational awareness (Sapci & Sapci, 2019; Timon et al., 2024; Wilmink et al., 2020). These domains represented intervention intensities ranging from routine coordination to potentially clinically consequential situations. Second, the scenarios depicted interactions among the platform, Mrs. Mija as an older adult, and her adult child. Routine interactions required limited user initiative while raising questions about consent, information sharing, explanation, confirmation, and family access.

Participants were asked to identify circumstances requiring explicit authorization or renewed confirmation. Third, the scenarios were rendered as illustrated panels situated in everyday contexts, consistent with design-probe and scenario-based methods (Lindsay et al., 2012; Mattelmäki, 2006). Panels were presented sequentially, with initial open responses followed by focused probes designed to clarify and deepen participants' accounts (Robinson, 2023).

Table 4 Scenario Probe Content and Design Tensions

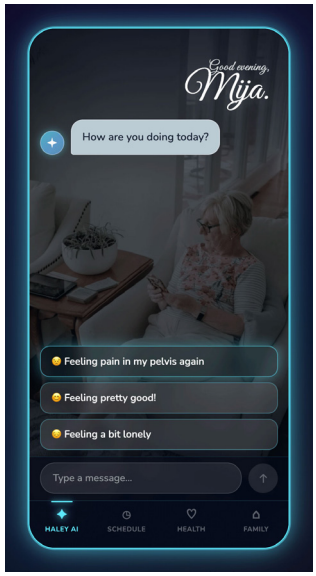
Screen	Depicted Situation	Design Tension Probed
S1	Daily emotional check–in with response options	Supportive check–in vs. intrusive solicitation of emotional or health information
S2	AI response to reported pelvic pain, with an offer to locate appropriate care	Helpful care navigation vs. clinical overreach
S3	Presentation of nearby providers and appointment–booking options	Convenience vs. explainability, informed choice, and provider verification
S4	Automatic schedule update following appointment selection	Seamless coordination vs. confirmation and user control
S5	Integrated daily plan covering medication, activity, meals, and care	Coordination support vs. cognitive load and behavioral pressure
S6	User–configured medication, activity, or appointment reminder	Reminder usefulness vs. autonomy and configurability
S7	Mood rating followed by encouraging feedback and daily highlights	Emotional reassurance vs. anthropomorphic persuasion
S8	Response to loneliness linked to patterns of family contact	Relational concern vs. surveillance and sensitive inference
S9	Community–activity suggestion following disclosure of loneliness	Social–connection support vs. algorithmic steering and unwanted disclosure
S10	Private self–soothing activities suggested following disclosure of loneliness	Personalized reassurance vs. emotional profiling and over–personalization
S11	Dashboard connecting the older adult with family members and clinicians	Integrated care coordination vs. role boundaries, access permissions, and data visibility
S12	Message history accompanied by AI–generated suggestions to contact a family member	Communication support vs. AI influence, unwanted prompting, and relational pressure
S13	AI–mediated notification of an incoming call from an adult child	Communication facilitation vs. interruption and older–adult agency
S14	Progress display showing completed and upcoming daily activities	Routine visibility vs. judgment and monitoring burden
S15	Wellness score accompanied by current health indicators	Actionable overview vs. reductive scoring and data opacity
S16	Weekly trends in vital signs, activity, sleep, and medication adherence	Longitudinal legibility vs. false certainty and the need for clinical interpretation

Note: All 16 screens have been illustrated in Appendix 3.

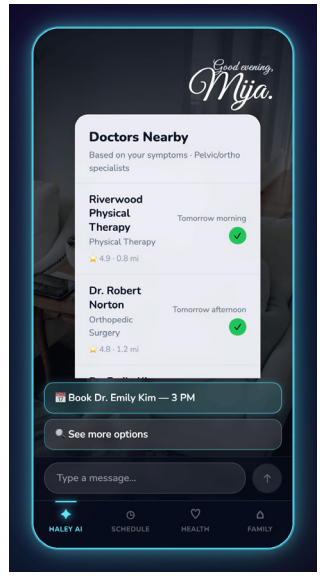
The walkthrough followed a service journey in which Mrs. Mija reported a mood or symptom, received care options, reviewed schedules and reminders, viewed summarized health and routine information, and could prompt family communication following a change in usual contact patterns. Figure 2 presents six representative screens, and Table 4 maps all 16 screens to their intended design tensions. The complete screen set appears in Appendix 3 and the standardized interview protocol in Appendix 4.

Interviews lasted approximately 40–60 minutes, were conducted by video call, audio-recorded with consent, and transcribed for analysis. Participants described their parents' health context, technology use, and caregiving involvement before reviewing the scenarios. Discussion addressed usefulness, trust, privacy, relational boundaries, governance, and

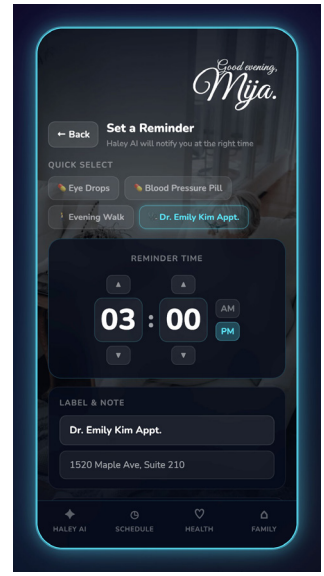
family coordination. Interviews concluded with proposed revisions, safeguards, alternative functions, and conditions for recommending or rejecting the platform.



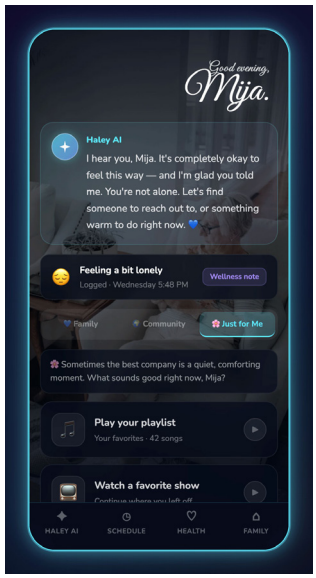
S1. Daily emotional check–in with response options



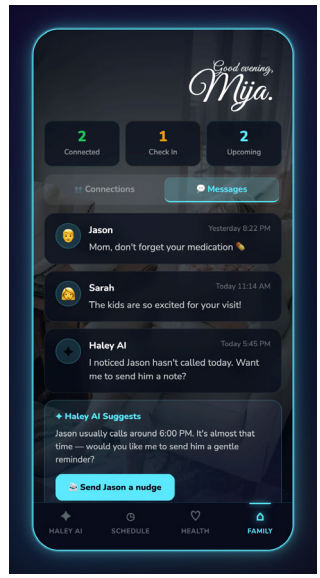
S3. Nearby providers and appointment–booking options



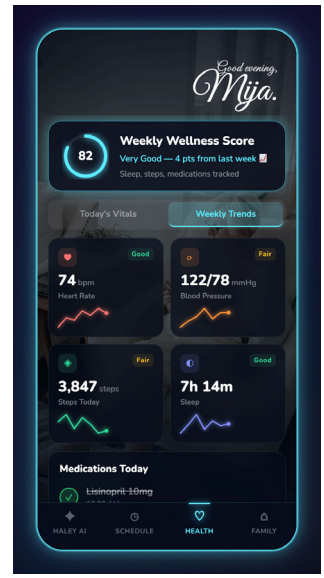
S6. User–configured medication, activity, or appointment reminder



S10. Private self–soothing activities suggested following disclosure of loneliness



S12. Message history with AI–generated suggestions to contact a family member



S16. Weekly trends for vital signs, activity, sleep, and medication adherence

Figure 2 Representative Mrs. Mija Scenario Screens Used as Design Probes
(See Appendix 3 for all 16 screens and Appendix 4 for the standardized interview protocol)

3. 3. 3. Qualitative Analysis

The interview transcripts were analyzed using Saldaña's (2021) two-cycle coding approach. First-cycle analysis used descriptive, in vivo, process, and values codes to identify meanings related to caregiving roles, platform evaluation, anticipated usability, trust, privacy, dignity, control, and family coordination. During the second cycle, pattern coding consolidated the

preliminary codes into higher-order categories and themes. The progression from first-cycle codes to pattern clusters and themes is documented in Figure 4 and Section 4.2.

Table 5 Cohen's Kappa Coefficient Formula and Notation

$\kappa = (Po - Pe) / (1 - Pe)$		
Symbol	**Term**	**Definition**
κ	Cohen's kappa coefficient	Measure of inter-coder agreement corrected for chance (Cohen, 1960)
Po	Observed proportional agreement	(a + d) / N
Pe	Expected agreement by chance	$[(a+b)(a+c) + (c+d)(b+d)] / N^2$
N	Total segments coded	30 (randomly selected from the corpus of 16 interview transcripts)
a	Both coders assigned code 1	Agreement on presence: Coder 1 = 1, Coder 2 = 1
b	Only Coder 1 assigned code 1	Disagreement: Coder 1 = 1, Coder 2 = 0
c	Only Coder 2 assigned code 1	Disagreement: Coder 1 = 0, Coder 2 = 1
d	Both coders assigned code 0	Agreement on absence: Coder 1 = 0, Coder 2 = 0

Table 6 2 × 2 Contingency Matrix

	C2 = 1	C2 = 0	C1 Total
C1 = 1	a	b	a + b
C1 = 0	c	d	c + d
C2 Total	a + c	b + d	N = 30

Table 7 Agreement Benchmarks (Landis & Koch, 1977)

κ Range	Interpretation
0.00 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost perfect

Inter-coder agreement was assessed across multiple coding rounds using Cohen's kappa (Cohen, 1960). The assessment used 30 segments randomly selected from the corpus of 16 interview transcripts. Table 5 defines the coefficient and notation, Table 6 presents the binary contingency structure used to calculate agreement, and Table 7 provides the Landis and Koch (1977) interpretation benchmarks. Codebook refinement and coder discussion occurred between rounds. Figure 3 reports the progression of kappa values, and the final code set reached substantial agreement, with mean $\kappa = .75$. Consistent with Warrens (2014), kappa was interpreted in relation to the coding design and observed agreement rather than a self-interpreting indicator.

Code	Unified label	a	b	c	d	Po	Pe	R1 κ	R2 κ	R3 κ	Final Level
UC1	Conditional trust	5	2	1	22	.900	.660	.394	.706	.706	substantial
UC2	Ambient monitoring preference	3	3	0	24	.900	.740	.535	.535	.615	substantial
UC3	Notification calibration	2	0	1	27	.967	.847	.630	.783	.783	substantial
UC4	Guilt-relief caregiver dialectic	4	1	1	24	.933	.722	.760	.760	.760	substantial
UC5	Relational boundary preservation	5	0	1	24	.967	.700	.586	.586	.889	Almost perfect
UC6	Elder autonomy and dignity	4	2	1	23	.900	.700	.667	.667	.667	substantial
UC7	Epistemic and clinical safety	7	0	1	22	.967	.624	.911	.911	.911	Almost perfect
UC8	Multilingual caregiving coordination	3	1	0	26	.967	.793	.839	.839	.839	Almost perfect
UC9	Accountability and system transparency	5	2	0	23	.933	.678	.793	.793	.793	substantial
UC10	Adjustable visibility and participatory-design control	4	4	1	21	.833	.656	.516	.516	.516	Moderate
Mean (All 10 codes)						.933	.712	.663	.710	.748	substantial

Figure 3 Inter–Coder Agreement Across Coding Rounds (Cohen, 1960; Landis & Koch, 1977)

3. 4. Integration

The quantitative and qualitative phases were integrated at the level of interpretation (Creswell & Plano Clark, 2018; Fetters et al., 2013). Integration focused on four quantitative patterns: the strong association between anticipated usability and perceived wellbeing; the statistically significant indirect effect involving eHealth literacy and anticipated usability; the persistence of the directional pattern after semantically proximate items were removed; and the selected similarities and differences between the two role groups. The nonsignificant moderation result and limited discriminant validity between anticipated usability and perceived wellbeing were also incorporated as constraints on interpretation. The qualitative findings were used to explain what participants placed within broad prospective judgments of platform usability and wellbeing, including expectations concerning family relationships, verification, consent, dignity, control, and intervention boundaries. The integrated interpretation is presented in Section 5.1.

Table 8 Factor Loadings, Eigenvalues, and Reliability by Construct

		Anticipated Usability				
Item	h^2	UE	UF	US	Eigenvalue	Var (%)
UE1	.793	.635				
UE2	.901	.800			2.457	30.715
UE3	.878	.778				
UF1	.839		.699			
UF2	.887		.760		2.422	30.275
UF3	.869		.762			
US1	.916			.807	2.109	26.360
US2	.905			.793		
						Total Var (%) = 87.350

Perceived Wellbeing								
Item	h^2	WP	WE	WR	WM	WA	Eigenvalue	Var (%)
WP1	.852	.726					1.737	17.370
WP2	.885	.757						
WE1	.871		.678				1.791	17.910
WE2	.920		.695					
WR1	.875			.667			1.808	18.080
WR2	.933			.802				
WM1	.887				.679		1.769	17.690
WM2	.882				.671			
WA1	.906					.726	1.804	18.040
WA2	.898					.767		
							Total Var (%) = 89.090	

eHealth Literacy						
Item	h^2	LN	LE	LA	Eigenvalue	Var (%)
LN1	.735	.857				
LN2	.781	.884			2.273	28.413
LN3	.757	.870				
LE1	.756		.870			
LE2	.812		.901		2.321	29.013
LE3	.753		.868			
LA1	.692			.832	1.352	16.900
LA2	.660			.813		
					Total Var (%) = 74.326	

Note: UE = Effectiveness; UF = Efficiency; US = Satisfaction; WP = Positive Emotion; WE = Engagement; WR = Relationships; WM = Meaning; WA = Accomplishment; LN = Navigation; LE = Evaluation; LA = Application. KMO values were .937, .958, and .915, respectively; all Bartlett's tests were significant at $p < .001$. Cronbach's α values were .953, .966, and .950, respectively.

4. Results

4. 1. Quantitative Findings

RQ1 examined the relationships among anticipated usability, eHealth literacy, and perceived wellbeing following exposure to the proposed invisible AI health platform. Analyses addressed measurement quality and discriminant validity, regression and indirect effects, semantic-overlap sensitivity, moderation, and role-based comparisons. Because the measurements were prospective self-reports collected at one time point, results are interpreted as associations rather than causal effects.

4. 1. 1. Measurement Quality and Discriminant Validity

Internal consistency was high for anticipated usability (α = .953), perceived wellbeing (α = .966), and eHealth literacy (α = .950). KMO values exceeded .90, and Bartlett's tests were significant ($p < .001$), supporting factor analysis. Table 8 reports the exploratory factor results. The very high alpha coefficients also suggested possible item redundancy and were therefore considered alongside tests of discriminant validity.

Table 9 Discriminant Validity and CFA Model Comparison

Test	AU	PW	Criterion	Results
AVE	.725	.739	〉.50	Supported
√AVE	.851	.860	〉φ = .914	Not supported
HTMT	.919	.919	〈.85 / 〈.90	Not supported
Composite–score r	.883	.883	〈.85	Not supported

CFA model	x^2(df)	CFI	TLI	RMSEA	SRMR
One factor	986.15 (135)	.888	.874	.130	.049
Two factors	686.01 (134)	.928	.917	.105	.045

Note: AU = anticipated usability; PW = perceived wellbeing; AVE = average variance extracted; HTMT = heterotrait–monotrait ratio. CFA used normal–theory maximum likelihood with the five–point items treated as continuous. Harman's unrotated first component explained 71.75% of total variance. Because this diagnostic is limited and the first–component share exceeded 50%, common–method variance cannot be ruled out.

Zero-order correlations were positive between anticipated usability and perceived wellbeing (r = .883), anticipated usability and eHealth literacy (r = .220), and eHealth literacy and perceived wellbeing (r = .161). The anticipated usability–perceived wellbeing correlation exceeded the .85 screening threshold. A two-factor CFA separating the constructs fit significantly better than a one-factor model, $\Delta\chi^2(1) = 300.14$, $p < .001$, but retained a high latent correlation ($\varphi = .914$) and inadequate RMSEA. Although AVE exceeded .50 for both constructs, neither square root of AVE exceeded the latent correlation. HTMT was .919, exceeding both the strict .85 and permissive .90 thresholds. Convergent validity was supported, but discriminant validity between anticipated usability and perceived wellbeing was not.

4. 1. 2. Regression, Mediation, and Sensitivity Analysis

eHealth literacy was positively associated with anticipated usability ($\beta = .220$, $p < .001$, $R^2 = .048$) and perceived wellbeing ($\beta = .161$, $p = .002$, $R^2 = .026$). When both predictors were entered, anticipated usability was strongly associated with perceived wellbeing ($\beta = .891$, $p < .001$), while the direct coefficient for eHealth literacy was small and nonsignificant ($\beta = -.034$, $p = .310$). The model explained 78.1% of the variance in perceived wellbeing. Given the limited discriminant validity, the anticipated usability coefficient should not be interpreted as a distinct causal effect.

PROCESS Model 4 with 5,000 bootstrap samples produced a statistically significant unstandardized indirect effect of eHealth literacy on perceived wellbeing through anticipated usability (B = .2304, Boot SE = .0672, 95% CI [.098, .362]). The cross-sectional design does not establish temporal or causal mediation. Because the indirect effect exceeded the total effect and the direct coefficient changed sign, no conventional proportion mediated or full-mediation claim was made.

Table 10 Sensitivity Analysis Excluding Semantically Proximate Items

Effect / fit	Full scales	Items excluded	Change
eHL → AU (β)	.220	.221	+.001
AU → PW (β)	.891	.874	−.017
eHL → PW, c′ (β)	−.034	−.037	−.003
Indirect effect (standardized)	.196 [.086, .307]	.193 [.084, .303]	−.003
R^2 for perceived wellbeing	.781	.750	−.031

Note: Excluded items were UF2, WE2, and WA2. Confidence intervals are percentile intervals from 10,000 nonparametric bootstrap samples.

Sensitivity analysis excluded UF2, WE2, and WA2. The standardized anticipated usability–perceived wellbeing coefficient decreased from .891 to .874, while the standardized indirect effect changed from .196, 95% bootstrap CI [.086, .307], to .193, 95% CI [.084, .303]. Model R^2 decreased from .781 to .750. Thus, the positive association and indirect-effect estimate persisted after item removal, although the remaining measurement overlap continued to limit interpretation.

4. 1. 3. Moderation Analysis

PROCESS Model 1 tested whether eHealth literacy moderated the association between anticipated usability and perceived wellbeing. As shown in Table 11, the interaction was not statistically significant (B = .044, β = .042, p = .090). The full moderation model explained 78.3% of the variance in perceived wellbeing, $F(3, 371) = 445.60$, $p < .001$. Variance inflation factors were below conventional thresholds, and the Durbin–Watson statistic was 1.617.

Table 11 Moderation Analysis

Predictor	B	SE	β	t	p	VIF
Constant	−.090	.140	—	−.642	.522	—
eHealth literacy	−.020	.031	−.017	−.654	.513	1.091
Anticipated usability	.989	.028	.881	35.071	〈.001	1.079
eHL × usability	.044	.026	.042	1.700	.090	1.061

Note: R^2 = .783; adjusted R^2 = .781; $F(3, 371) = 445.603$, p 〈 .001; Durbin–Watson = 1.617.

4. 1. 4. Role–Based Comparison and Measurement Invariance

The empirical basis for pooled analysis was evaluated using sequential multigroup CFA. Relative to the configural model, metric constraints produced a negligible change in fit (ΔCFI = −.001; ΔRMSEA = −.001), and scalar constraints produced similarly limited deterioration (ΔCFI = −.004; ΔRMSEA < .001). These changes satisfied conventional change-in-fit criteria. However, the configural model's CFI and TLI were marginal (CFI = .888; TLI = .877), so the evidence for cross-group measurement equivalence was qualified rather than unequivocal.

Anticipated usability did not differ by age-operationalized group membership. The adult child group reported higher perceived wellbeing and lower eHealth literacy than the baby boomer group, although the perceived wellbeing difference was modest and nominally significant (p = .032). The combined construct profile differed across groups, Hotelling $T2 = 27.57$, $F(3, 371) = 9.14$, permutation $p < .001$.

The anticipated usability–perceived wellbeing path was strong in both groups and larger among baby boomers; the bootstrap confidence interval for the group difference narrowly excluded zero. Confidence intervals for group differences in the eHealth literacy–anticipated usability path, direct effect, and indirect effect included zero. Pooled analysis was therefore supported at the measurement level but did not imply complete structural or evaluative equivalence.

Across the pooled, sensitivity, and group-specific analyses, anticipated usability maintained a strong positive association with perceived wellbeing. However, their high shared variance and common prospective framing limit claims of construct distinctiveness and causal mediation. The quantitative findings are therefore carried forward as evidence of a consistent positive association and statistically significant indirect-effect estimate, with measurement overlap and role-based heterogeneity incorporated into the qualitative interpretation in Section 4.2.

Table 12 Construct Comparisons, Measurement Invariance, and Group–Specific Paths by Age–Operationalized Group

Panel A. Construct Means

Construct	Adult children M (SD)	Baby boomers M (SD)	BB − AC	p	d
Anticipated usability	3.74 (.76)	3.71 (1.04)	−.04	.678	−.04
Perceived wellbeing	3.65 (.85)	3.43 (1.17)	−.22	.032	−.21
eHealth literacy	3.57 (.87)	3.90 (.83)	.34	〈.001	.40

Panel B. Measurement Invariance

Model	x^2 (df)	CFI	TLI	RMSEA	SRMR	⊿CFI
Configural	1800.07 (592)	.888	.877	.074	.060	—
Metric	1838.29 (615)	.887	.880	.073	.061	−.001
Scalar	1908.28 (638)	.883	.880	.073	.061	−.004

Panel C. Group–Specific Standardized Paths

Path	Adult children	Baby boomers	BB − AC	95% CI for difference
eHL → AU	.371	.161	−.210	[−.459, .038]
AU → PW	.824	.909	.085	[.004, .191]
eHL → PW, c′	.029	−.031	−.060	[−.194, .060]
Indirect effect (ab)	.306	.146	−.159	[−.367, .055]

Note: AC = adult children; BB = baby boomers. Mean comparisons use Welch independent-samples tests. Path-difference intervals are based on 10,000 bootstrap samples. Approximate invariance was evaluated using ΔCFI and ΔRMSEA.

4. 2. Qualitative Findings

RQ2 examined how adult children interpreted, evaluated, and redesigned the proposed invisible AI health platform in relation to their caregiving experiences. The scenario-development process and interview sequence are described in Section 3.3.2 and are not repeated as findings. Following Saldaña's (2021) two-cycle coding approach, first-cycle descriptive, in vivo, process, and values codes were consolidated through pattern coding into four themes. Figure 4 documents the progression from code clusters to themes, while the full codebook in Appendix 1 reports code definitions, participant coverage, quotations, and pattern assignments. Code contributions were not necessarily exclusive because some relational and coordination codes informed more than one theme. Inter-coder assessment of the final code set indicated substantial agreement (mean $\kappa = .75$).



Figure 4 Two-Cycle Coding Progression Following Saldaña (2021)
(See Appendix 1 for full first-cycle code inventory)

4. 2. 1. Invisible AI as a Relational Support Layer

The first theme linked codes concerning conditional reassurance and relational ambivalence (A2, A3, A5–A15) with codes concerning preserved family communication and reciprocal care (D5–D11). The shared pattern was not simple enthusiasm for automation. Participants accepted invisible AI when it strengthened an existing relationship while remaining visibly subordinate to it. P8 likened the desired platform to "a child's daily phone call—checking mood and health," whereas P6 described the preferred arrangement as "not stopping my care—parallel use for better synergy." These accounts framed AI as continuity infrastructure: useful because it kept family members informed without transferring the meaning of care to the system.

Responses varied with relationship quality, distance, and participants' emotional stance toward caregiving. P5 anticipated a "strong sense of relational distance from my parents" if AI displaced direct contact, and P7 summarized the contingency as "Good relationship = reassurance. Poor relationship = burden." A contrasting case came from P9, who reported "no feelings at all," indicating that some participants evaluated the platform primarily through a professional or functional lens.

Other accounts complicated a purely instrumental interpretation. P10 valued the possibility of a private disclosure space for older adults, describing it as "good to share things you can't openly tell your children—in detail. Comfortable." Together, these cases showed that relational value depended on fit with a particular family arrangement rather than on AI presence alone.

4. 2. 2. Trust Through Verification, Trialability, and Bounded Claims

The second theme connected clinical and epistemic safety codes (B2–B8, B16–B18) with codes concerning trialability, institutional assurance, and gradual trust formation (B9–B15). Across professional backgrounds, participants treated trust as established through evidence and constrained system behavior. P1 required that "all services must be clinically or safely verified," while P12 and P13 preferred that the system acknowledge uncertainty: "Rather the AI say I don't know than to give misinformation."

P15 similarly wanted direct experience before family adoption: "Allow me to use it myself first—free trial before recommending." These responses tied trust to verification, uncertainty disclosure, and opportunities for testing rather than generalized claims of AI capability.

Participants differed in the assurances they considered persuasive. P6 emphasized accumulation over time—"Trust should accumulate over time. Supplementary use is ideal"—whereas P16 used institutional reputation as a security proxy: "If it has blue-chip names like Google or Samsung, I'd trust the security." By contrast, P11's deployment experience supported a skeptical position: "The quality of generative AI is not yet at par for B2C health use." Trust could therefore draw on personal testing, clinical endorsement, institutional reputation, or accumulated experience. Across these routes, participants emphasized that system claims, uncertainty, and escalation boundaries should remain inspectable.

4. 2. 3. Surveillance and Dignity as the Ethical Boundary

The third theme drew on the objective-subjective information boundary (B7), privacy and monitoring codes (C1–C13), and governance codes assigning control and consent across generations (D1–D4). Participants distinguished factual health observation from interpretation of emotions or family relationships. P7 described subjective emotional inference as feeling "like a shackle," while P2, P8, and P14 stated that "family agreement on what is shared must come first." These responses located dignity not only in data security but in control over what the platform inferred, communicated, and made actionable.

The boundary was contested rather than unanimous. P16 acknowledged, "I'd want to monitor conversations, even though my parents may not like it," exposing tension between caregiver reassurance and older adult autonomy. The same participant reported, "He thought the watch was bulky and stopped. He refuses to install CCTV," illustrating how monitoring can be rejected when experienced as burdensome or intrusive. P4 warned that "overtrusting AI could mean missing the golden window in a real emergency," while P11 feared AI "acting on its own maliciously." Across these accounts, acceptable monitoring was described as observable, consented to, proportionate, and reversible rather than covert, coercive, or substitutive for human judgment.

4. 2. 4. Minimum Viable Intervention for Family Coordination

The fourth theme integrated minimalist interaction, configurable social form, and functional-specialization codes (F1–F8, F11–F18) with reciprocal coordination codes (D5–D9). Participants repeatedly reduced the proposed platform from a broad AI companion to a limited set of dependable functions. P2, P3, P4, and P14 requested "fewer features—one-click health management." P4, P7, P14, and P15 prioritized "reminders, medication alerts, and admin coordination," while P1 identified "duplicate medication checking—a patient safety priority." P11 placed AI below human authority: "If AI can connect to a human specialist for a second layer—that's the right model." These responses converged on the least intrusive intervention capable of reducing coordination failure.

Preferences concerning social interaction varied. P3 and P16 stated that "friend-like AI conversation feels uncomfortable—just give me the bio data," favoring passive monitoring and exception-based alerts. In contrast, P10 imagined "a conversation partner that receives what elders won't tell children," and P6 proposed allowing older adults to choose a trusted face or voice. Participants therefore did not reject warmth or conversation categorically; they rejected compulsory anthropomorphism and unbounded social presence. Administrative coordination and clinically grounded safety functions formed the common functional core, while conversational features required choice, limited scope, and the ability to withdraw.

5. Discussion

5. 1. Integrated Interpretation of Findings

RQ3 asked what the integrated findings suggest about the acceptability of invisible AI health platforms in intergenerational care. The survey identified patterns in prospective

platform evaluations, while the interviews showed how adult children interpreted specific functions, risks, and caregiving arrangements. The qualitative findings therefore illuminate the meanings surrounding the quantitative constructs but do not establish the statistical mechanism underlying their associations.

Anticipated usability remained strongly associated with perceived wellbeing in the full and reduced-item analyses. However, the high composite and latent correlations, failed discriminant-validity criteria, and common prospective framing indicate that respondents did not clearly distinguish expected system manageability from expected psychosocial benefit. The
relationship is best interpreted as a broad positive evaluation of the proposed platform rather than evidence that usability independently produces wellbeing. Removing three semantically proximate items showed that the association was not attributable solely to those items, but it did not resolve the remaining measurement overlap.

The interviews clarified what adult children considered when evaluating the platform. Their judgments extended beyond interface simplicity and functional efficiency to whether the system supported existing relationships, provided verifiable information, preserved older-adult agency, and facilitated family coordination without excessive intervention. These considerations should not be treated as dimensions statistically recovered from the survey; they were generated through a separate qualitative analysis.

The eHealth literacy findings also require restraint. eHealth literacy was associated with anticipated usability and had a significant indirect effect estimate through anticipated usability, but its direct coefficient was nonsignificant when anticipated usability was included. The eHealth literacy × anticipated usability interaction was also nonsignificant. Qualitative emphasis on verification and uncertainty offers a plausible interpretive connection to eHealth literacy, but this connection was not directly tested.

Change-in-fit criteria provided qualified support for pooling the age-operationalized groups, although configural fit was marginal and selected mean and path differences remained. Because the dataset lacked a direct role variable, these patterns should be interpreted as comparisons between age-classified groups rather than verified parent-child differences.

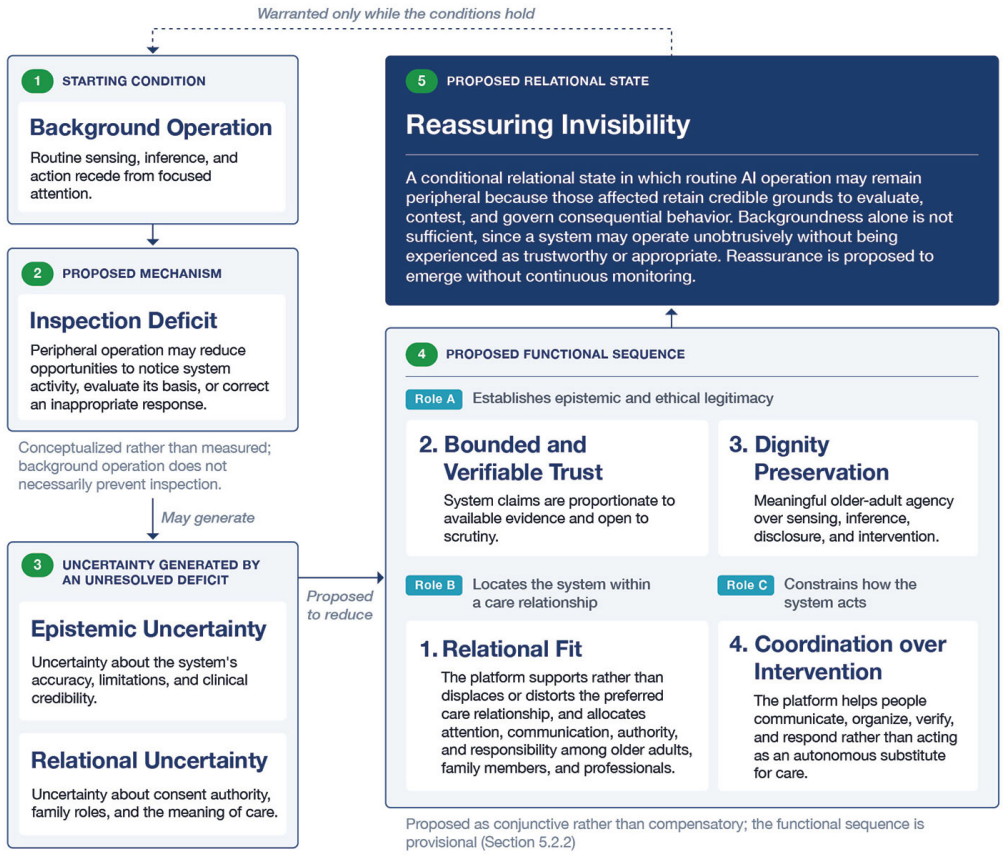
Taken together, the findings suggest that the acceptability of background AI is conditional. Reduced attentional demand may be beneficial, but background operation becomes problematic when it limits the ability to assess accuracy, control information flows, preserve family roles, or interrupt inappropriate action. Conversely, visibility alone is insufficient: an understandable system may still be intrusive, disproportionate, or relationally misaligned. This tension provides the basis for reassuring invisibility.

5. 2. Theorizing Reassuring Invisibility

5. 2. 1. From Background Operation to Conditional Reassurance

As illustrated in Figure 5, this study proposes reassuring invisibility as a relational state in which routine AI operation may remain peripheral because consequential behavior remains

sufficiently evaluable, contestable, and governable. The concept distinguishes technical backgroundness from acceptable invisibility. A system may operate unobtrusively without being experienced as trustworthy or appropriate.



Note. The four conditions are proposed to operate conjunctively rather than compensatorily; strength in one condition is not assumed to offset weakness in another. Both the conjunctive relationship and the sequence shown are theoretical propositions that were not tested empirically in this study. Conditions are numbered as presented in Section 5.2.2 and grouped by their proposed functional role.

Figure 5 From Background Operation to Reassuring Invisibility

When sensing, inference, or action recedes from attention, users may have fewer opportunities to notice system activity, evaluate its basis, or correct an inappropriate response. The study conceptualizes this potential reduction as an inspection deficit. The deficit is not directly measured, nor does background operation necessarily prevent inspection. Notifications, logs, explanations, confirmations, and human escalation can return consequential activity to focused attention. The central issue is whether adequate routes exist from peripheral operation to inspection and control.

An unresolved inspection deficit may generate epistemic uncertainty about accuracy, limitations, and clinical credibility, as well as relational uncertainty about consent authority, family roles, and the meaning of care. Reassurance is proposed to emerge when four conditions reduce these uncertainties without requiring continuous monitoring of the system.

This formulation builds on calm technology, which already emphasizes movement between the center and periphery of attention. Reassuring invisibility adds an intergenerational governance question: who may bring system activity into focus, under what circumstances, and with what authority to inspect, contest, modify, or stop it?

5. 2. 2. Four Conditions of Reassuring Invisibility

Relational fit concerns whether the platform supports rather than displaces or distorts the preferred care relationship. The same function may reassure one family while creating guilt, pressure, or distance in another. Relational fit depends on how the system allocates attention, communication, responsibility, and authority among older adults, family members, and professionals.

Bounded and verifiable trust concerns whether system claims are proportionate to available evidence and open to scrutiny. Participants emphasized clinical verification, acknowledgment of uncertainty, trialability, accumulated experience, and access to human expertise. Trust depended on identifiable limits: what the platform knows, what it does not know, when it must defer, and how consequential recommendations can be checked.

Dignity preservation concerns meaningful older-adult agency over sensing, inference, disclosure, and intervention. Data security alone is insufficient if a platform infers emotions without consent, creates asymmetrical family access, or enables coercive monitoring. Dignity preservation therefore includes understandable consent, differentiated permissions, selective sharing, reversibility, auditability, and the ability to refuse certain functions.

Coordination over intervention concerns whether the platform primarily helps people communicate, organize, verify, and respond rather than acting as an autonomous substitute for care. Participants favored reminders, appointment support, medication checks, summarized information, and routes to human expertise over expansive AI companionship or independent decision-making. The condition prioritizes the least intrusive system action capable of addressing a concrete coordination need.

The study proposes that these conditions may operate conjunctively rather than as interchangeable benefits. Convenience cannot compensate for nonconsensual monitoring, and strong privacy protection cannot compensate for clinically unverifiable advice. However, their joint necessity and non-compensatory operation were not empirically tested. They remain theoretical propositions for future validation.

The conditions may also form a provisional functional sequence. Bounded and verifiable trust and dignity preservation establish epistemic and ethical legitimacy. Relational fit locates the system within a particular care relationship. Coordination over intervention constrains how that system acts. This sequence should remain provisional until tested across different technologies, relationships, and levels of clinical risk.

5. 2. 3. Relationship to Adjacent Concepts

Reassuring invisibility extends rather than replaces existing traditions (Table 13). Calm technology addresses movement between peripheral and focused attention (Case, 2015; Weiser & Brown, 1996), while ambient intelligence emphasizes embedded sensing and context-aware responsiveness (Aarts & Wichert, 2009). Privacy-by-design provides proactive safeguards, privacy-preserving defaults, transparency, lifecycle protection, and user control (Cavoukian et al., 2010; Langheinrich, 2001).

Table 13 Positioning Reassuring Invisibility in Relation to Adjacent Concepts and Design Qualities

Concept or design quality	Primary concern	Contribution to background AI	What it does not address alone	Relationship to reassuring invisibility
Calm Technology (Weiser & Brown, 1996)	Management of human attention	Places routine interaction at the periphery while bringing relevant information to attention when needed	Does not fully specify how peripheral operation becomes acceptable within unequal or interdependent care relationships	Provides the attentional foundation; reassuring invisibility adds relational, epistemic, and governance conditions
Ambient Intelligence (Aarts & Wichert, 2009)	Context–aware environmental responsiveness	Enables sensing and adaptive support without continuous user commands	Responsiveness may remain opaque, socially misaligned, or disproportionate to the care need	Provides the infrastructural setting; reassuring invisibility specifies the conditions under which ambient responsiveness is relationally warranted
Privacy–by–Design (Cavoukian et al., 2010; Langheinrich, 2001)	Proactive protection of personal data	Embeds privacy safeguards, data minimization, and user control into system architecture	Privacy protection alone does not establish clinical credibility, relational fit, or appropriate intervention boundaries	Contributes to Dignity Preservation, while reassuring invisibility also requires relational fit, verifiability, and restrained intervention
Seamlessness (Chalmers & Galani, 2004)	Reduction of interactional friction	Simplifies transitions, minimizes effort, and supports continuity of use	Excessive seamlessness can remove necessary moments of confirmation, explanation, consent renewal, or contestation	Reassuring invisibility preserves low–friction routines but introduces deliberate friction at consequential moments
Legibility (Markus et al., 2021)	Ability to understand system behavior	Makes data use, reasoning, uncertainty, and actions more perceptible or explainable	A legible system may still be intrusive, relationally inappropriate, or excessively interventionist	Supports Bounded and Verifiable Trust but remains one condition within a broader relational account
Reassuring Invisibility (Present study)	Relationally warranted background operation	Explains when users can allow routine AI activity to remain peripheral while retaining meaningful control over consequential behavior	Its proposed conditions and non–compensatory structure require validation across populations, technologies, and levels of clinical risk	Integrates four conditions: Relational Fit, Bounded and Verifiable Trust, Dignity Preservation, and Coordination over Intervention

Note: The limitations and relationships presented in the final two columns are the authors' synthesis.

Seamlessness and legibility are treated as cross-cutting design qualities rather than unified theoretical traditions. Seamlessness concerns continuity of interaction and the management of perceptible boundaries, whereas legibility concerns users' ability to understand system behavior and its basis (Chalmers & Galani, 2004; Markus et al., 2021). Reassuring invisibility requires neither complete frictionlessness nor continuous visibility. Routine operation may remain unobtrusive, while explanation, confirmation, consent renewal, or human review introduces deliberate friction at consequential moments.

The proposed concept therefore asks an integrative question: under what conditions is it warranted for consequential AI activity to remain peripheral within a care relationship characterized by distributed responsibility?

5. 2. 4. Scope, Boundaries, and Testability

Reassuring invisibility applies most directly to routine monitoring and coordination functions such as reminders, scheduling, health summaries, and exception-based notifications. It does not justify invisibility in autonomous diagnosis, unsupervised emergency intervention, involuntary surveillance, or other decisions requiring immediate professional accountability.

Family involvement is likewise not inherently reassuring. Relationships may be supportive, distant, coercive, abusive, or contested. Where family authority threatens an older adult's interests, independent safeguards and professional oversight must take priority over caregiver convenience.

The qualitative variation also indicates that no single social form will be appropriate for all users. Some participants welcomed a conversational companion or customizable face and voice, while others preferred functional summaries and exception-based alerts. Socially expressive features should therefore be chosen, bounded, reversible, and subordinate to the user's preferred relationships.

Future research can measure inspection deficit, the four conditions, perceived governability, and willingness to allow peripheral operation. Experiments can manipulate visibility, explanation, consent controls, relational framing, and intervention autonomy. Additive, interaction, threshold and necessary-condition models can then test whether weakness in one condition can be compensated for by strength in another. Longitudinal prototype studies should examine whether the conditions predict continued acceptance after errors, alerts, or changes in family responsibility. The concept would be weakened if peripheral operation remained equally acceptable without these conditions, if the conditions did not reduce perceived threat or increase governability, or if their effects proved entirely additive.

5. 3. Practical Implications for Invisible AI Health Platforms

Four practical implications follow from the findings. First, design differentiated access with ongoing consent. Older adults, family members, and professionals require coordinated but distinct views, graduated permissions, and clear sharing records. For example, the connection dashboard (S11), AI-nudge screen (S12), and incoming-call screen (S13) should allow older adults to authorize, preview, dismiss or reverse family access and communication. Consent should be revisited whenever data recipients, inference types, or escalation rules change.

Second, prioritize coordination over autonomous intervention. Platforms should begin with bounded functions such as appointment support (S2–S4), configurable reminders (S6), and routine tracking (S14). Symptom-related functions should disclose uncertainty, distinguish informational support from clinical advice, require confirmation for consequential actions, and provide access to qualified human review.

Third, make inferences and alerts inspectable. Health summaries and trend displays (S15–S16) should disclose data sources, update timing, missingness, uncertainty and alert thresholds. Mood, loneliness, and contact-pattern functions (S7–S13) require particularly explicit controls. Users should be able to disable sensitive inferences, understand why an alert was generated, correct errors, and determine who receives the information.

Fourth, make social presence optional and configurable. Conversational features should not be the default. Users should be able to select functional or conversational modes, adjust tone and frequency, modify or remove a face or voice, and withdraw from companion-like interaction without losing administrative or safety functions. This accommodates participants who welcomed an AI companion as well as those who preferred data summaries and exception-based alerts.

5. 4. Theoretical and Methodological Implications

The principal theoretical contribution is to connect attentional peripherality with relational and institutional accountability. Calm technology explains how information moves between peripheral and focused attention; reassuring invisibility specifies the conditions under which that movement may be warranted when authority and responsibility are distributed across older adults, family members, and professionals.

The study also refines the use of ambient intelligence in family care. Context awareness must include not only environmental and behavioral states but also family roles, consent arrangements, relationship quality and professional authority. For privacy-by-design, the findings emphasize that proactive protection and user control should extend to inferred emotional and relational information, differentiated family permissions, and intervention boundaries.

Methodologically, the study shows the value of combining prospective survey analysis with participatory design interviews and disconfirming cases. The quantitative phase identified a strong but poorly differentiated association, while the qualitative phase revealed heterogeneous meanings obscured by pooled scores. The theoretical contribution therefore rests less on the magnitude of the regression coefficient than on the qualitative conditions and the limits revealed through integration.

A clear distinction must be maintained between empirical themes and theoretical synthesis. Relational support, bounded trust, dignity, and limited intervention were generated from the qualitative analysis. Inspection deficit, the four-condition structure, and the proposed non-compensatory mechanism are theoretical developments produced through integration and require further testing.

5. 5. Limitations and Future Research

Three principal limitations constrain the findings. First, measurement overlap and the cross-sectional design limit interpretation. Anticipated usability and perceived wellbeing lacked discriminant validity, and removing three semantically proximate items did not resolve their overlap. The prospective, single-survey design may also have inflated associations and cannot

establish temporal or causal mediation. Future studies should develop distinct functional and psychosocial measures, validate them in independent samples, and use longitudinal or experimental designs incorporating behavioral and functional data from prototype use.

Second, the samples and research setting limit generalizability. Quantitative groups were operationalized by age rather than verified caregiving roles, participants were not matched dyads, and configural fit was marginal. The qualitative phase included 16 adult children but no older adults and used illustrated scenarios during a single interview rather than a deployed platform. Future studies should recruit verified older adult and caregiver dyads, include diverse older adults and professionals, and examine functional prototypes through longitudinal field research.

Third, reassuring invisibility remains a context-bound theoretical proposal. The four conditions were not operationalized or tested as a measurement model, inter-coder agreement was assessed on 30 sampled segments, and cultural and linguistic variation was not modeled. Future research should test the conditions across levels of autonomy and clinical risk, compare additive and non-compensatory models, report broader coding-reliability evidence, and examine whether the framework generalizes across caregiving cultures, privacy expectations, and family-authority structures.

6. Conclusion

Invisible AI health platforms do not become acceptable simply by receding from attention. Their value depends on whether unobtrusive operation supports everyday care without weakening the ability of older adults and family members to understand, question, or redirect consequential behavior. The findings suggest that acceptability is shaped not by invisibility alone, but by how the platform fits the care relationship, establishes bounded and verifiable trust, preserves dignity, and prioritizes coordination over autonomous intervention.

Reassuring invisibility names this conditional state. A system may be technically unobtrusive by operating outside continuous attention, but it becomes acceptably invisible only through the relationships in which it is used. Its background operation must remain compatible with caregiving roles, preserve older-adult agency, and provide credible ways to verify or challenge consequential actions. Reassuring invisibility is therefore not achieved merely by hiding interaction; it is negotiated through trust, consent, accountability, and the continuing possibility of human intervention.

The concept applies most directly to routine monitoring and coordination rather than autonomous diagnosis, unsupervised emergency action, or involuntary surveillance. Its four conditions and proposed relationships remain to be tested with deployed platforms, direct older-adult participation, verified family dyads, and culturally varied samples. Within these boundaries, reassuring invisibility offers a relational account of when AI may remain peripheral and when it must return to attention, explanation, and human judgment.

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Appendix 1 Full First–Cycle Codebook (85 Codes and Clusters A to F)

Cluster A: Emotional Responses to AI–Mediated Care (15 codes)

Code	Label	Type	Definition	Quotes	Participants	Pattern
A1	AI as anti–loneliness companion	In vivo	Anticipation that AI presence reduces elder social isolation and emotional loneliness.	*"It would be nice — not to be lonely."*	P1, P8	PA
A2	Conditional reassurance (accuracy–dependent)	Process/ value	Reassurance is contingent on platform functioning reliably; breaks down if accuracy fails.	*"Reassurance only if the platform functions reliably."*	P1, P3, P4, P8, P12, P14	PA
A3	AI as synergistic complement to existing care	Process/ value	AI adds to, rather than replaces, existing caregiving effort; parallel use creates synergy.	*"Not stopping my care — parallel use for better synergy."*	P6, P8	PE
A4	Aging dependency reframed as achievement	Process/ value	AI can shift elder's emotional frame from dependency–induced depression toward positive achievement.	*"Achievement–oriented framing rather than depression of dependency."*	P6	PA
A5	Background worry reduction — diaspora–acute	Descriptive	AI reduces persistent low–grade anxiety about parents' safety; intensity heightened for geographically distant caregivers.	*"Never being the one who didn't know — especially acute for distant caregivers."*	P5, P8, P14	PG
A6	AI as child's daily phone–call equivalent	In vivo	Platform functions as a proxy for the affective continuity a daily call provides.	*"Like a child's daily phone call — checking mood and health."*	P8	PE
A7	AI as elder's trusted friend–like companion	In vivo	Elder's subjective experience of AI as a friend–like, non–clinical presence; validated across professional lenses.	*"Feels like a friend."*	P8, P9	PA
A8	Distance relief — AI as geographic care substitute	Descriptive	For diaspora caregivers, AI provides monitoring continuity that physical distance makes impossible.	*"Extra helping hand given I am distant — needed for rapid information access."*	P4, P5, P9, P12, P13	PG
A9	AI as elder safe–disclosure space	In vivo	AI receives elder concerns that cannot be told to family. Analytically novel: reframes platform from child–facing monitor to elder–facing confidant.	*"Good to share things you can't openly tell your children — in detail. Comfortable."*	P10	PA
A10	Ambivalent relief–guilt compound	Process/ value	Relief and caregiver guilt are simultaneously activated; cannot be separated.	*"Relieved and burdened at the same time — cannot feel one without the other."*	P5, P12, P15	PA
A11	Emotional distance / relational displacement fear	In vivo	Fear that AI presence creates emotional distance between elder and adult child.	*"Strong sense of relational distance from my parents."*	P5	PE
A12	AI as stress amplifier without trust	Process/ value	Without trust, AI monitoring intensifies caregiver anxiety rather than reducing it.	*"It may increase stress if I cannot trust the AI output."*	P11	PB
A13	Health concealment — AI passive detection opportunity	Descriptive	Elders suppress health problems to avoid burdening family; AI can detect what self–report conceals.	*"They'd probably hide it to not burden us."*	P16	PA
A14	Relationship quality as platform value moderator	Process/ value	Platform yields reassurance in good relationships; generates burden in poor ones.	*"Good relationship = reassurance. Poor relationship = burden."*	P7	PE
A15	No emotional response — professional detachment	Descriptive	Orthopedic professional reports no affective response to AI care substitution; clinical detachment.	*"No feelings at all."*	P9	PA

Cluster B: Trust Conditions — What Makes AI Trustworthy (18 codes)						
Code	Label	Type	Definition	Quotes	Participants	Pattern
B1	Familiarity and intuitive UX as pre-condition	Process/ value	AI must feel familiar before adoption; interface must be intuitive and require minimal learning.	*"Must feel familiar. Interface must be intuitive and easy."*	P1, P2, P3, P14	PB
B2	Clinical validation required for all services	Descriptive	ENT-physician standard: every service must be clinically validated or verified for safety before deployment.	*"All services must be clinically or safely verified."*	P1, P8	PH
B3	Medication duplication detection as safety feature	Descriptive	Duplicate medication checking is a high-value, low-AI-risk clinical function.	*"Duplicate medication checking — a patient safety priority."*	P1	PH
B4	Professional knowledge and communication competence	Process/ value	Orthopedic standard: trust requires both domain knowledge accuracy AND communication competence.	*"Trust requires professional knowledge and communication accuracy."*	P9	PH
B5	Evidence-based, expert-verified, transparent	Process/ value	Wellness instructor standard: information must be evidence-based, expert-verified, and honest.	*"Evidence-based, expert-verified, transparent and honest answers."*	P5	PB
B6	Fact-checking precision as epistemic trust standard	In vivo	Financial consultant standard: information must be fact-checked clearly before delivery.	*"Good if fact-checked clearly before information delivery."*	P10	PB
B7	Objective/ subjective information boundary (legal lens)	In vivo	Lawyer standard: factual sharing is warm and acceptable; subjective emotional inference is a shackle.	*"Factual sharing feels warm. Subjective emotional inference feels like a shackle."*	P7	PC
B8	Accuracy over confidence — admit uncertainty	In vivo	Epistemic honesty more valuable than a confident but wrong output.	*"Rather the AI say I don't know than to give misinformation."*	P12, P13	PB
B9	Family feedback loop as functional trust signal	Process/ value	Platform trust built through observable feedback to children about parents' daily wellness.	*"Feedback to children about parents' wellbeing builds sustained trust."*	P7	PB
B10	Personal trial before parent recommendation	Process/ value	Adult child must personally validate quality before recommending to parents.	*"Allow me to use it myself first — free trial before recommending."*	P15	PB
B11	Medical authority as elder adoption gateway	Descriptive	Physician endorsement is the most credible pathway for elder adoption.	*"If their doctors recommend it, they'd be willing to try."*	P15	PB
B12	Brand ethics / corporate mission as trust proxy	Process/ value	Corporate ethical stance substitutes for personal technical verification.	*"The parent company must communicate their mission and values."*	P11	PB
B13	Blue-chip institutional brand as security proxy	Descriptive	Institutional brand name substitutes for security assessment for non-technical users.	*"If it has blue-chip names like Google or Samsung, I'd trust the security."*	P16	PB
B14	Social proof and mass adoption as validation	In vivo	Mass adoption equals public endorsement and collective trust validation.	*"Mass adoption equals public recognition and approval."*	P6	PB
B15	Trust accumulates gradually — supplementary use ideal	Process/ value	Trust builds naturally over time; supplementary rather than primary role is the ideal starting position.	*"Trust should accumulate over time. Supplementary use is ideal."*	P6	PB

B16	AI quality skepticism from deployment experience	Process/ value	Professional B2C deployment experience generates evidence-based skepticism.	*"The quality of generative AI is not yet at par for B2C health use."*	P11	PB
B17	Fear of AI hallucination in health context	In vivo	Specific fear of AI fabricating health information that leads users toward harm.	*"How can I trust the AI isn't misdiagnosing or hallucinating?"*	P11	PB
B18	Convenience and sustainability as trust baseline	Process/ value	Convenient but unsustainable platform cannot be trusted as health infrastructure.	*"Convenience and sustainability must both be present."*	P2	PB

Cluster C: Privacy, Surveillance, and the Dignity Threshold (13 codes)

Code	Label	Type	Definition	Quotes	Participants	Pattern
C1	Contact frequency as shackle — legally precise threshold	In vivo	Too-frequent contact feels coercive; the frequency and manner of AI communication both matter.	"Too-frequent contact feels like a shackle."	P7	PC
C2	Emotional inference = privacy violation	In vivo	AI conveying emotional grievances is experienced as a privacy invasion by the elder.	"AI sharing emotional complaints feels like a privacy violation."	P7	PC
C3	AI as instrument of parental relational coercion	Process/ value	Emotionally immature parent could weaponize platform to pressure adult children.	"An immature parent could use this to pressure their children."	P7	PC
C4	Consent-driven sharing as privacy solution	Process/ value	Parental control over what is shared is the non-negotiable adoption prerequisite.	"Family agreement on what is shared must come first."	P2, P8, P14	PC
C5	Information overload as intrusion — feature aversion	Process/ value	Excessive features and unnecessary push notifications are unwelcome regardless of content.	"Too many features and unnecessary push notifications — I would decline those."	P4, P5	PF
C6	Data breach and commercial exploitation risk	Descriptive	Health data is commercially exploitable; platform must be independent from hospital marketing.	"Data could be commercially exploited. Must be independent from hospital ads."	P1, P6, P14	PC
C7	Phishing and fraud risk — adversarial exploitation	Descriptive	Financial consultant extends misuse typology from passive breach to active fraud: phishing and social engineering.	"Privacy exposure and phishing fraud — active adversarial risk."	P10	PC
C8	AI malicious autonomous agency fear	In vivo	Fear that AI could act adversarially of its own accord, not merely make errors.	"I'd be afraid of AI acting on its own maliciously."	P11, P12, P16	PC
C9	AI psychological manipulation / gaslighting risk	In vivo	If AI exploits psychological vulnerabilities, elder could become dangerously dependent.	"If AI exploits psychological vulnerabilities, the elder could become trapped."	P8	PC
C10	Child desires conversation monitoring despite tension	Process/ value	Adult child's desire to monitor conversations directly conflicts with elder privacy.	"I'd want to monitor conversations, even though my parents may not like it."	P16	PC
C11	Real-world elder tech rejection — Galaxy Watch + CCTV	Descriptive	P16 provides the only material real-world monitoring rejection in the corpus: abandoned smartwatch, refused CCTV.	*"He thought the watch was bulky and stopped. He refuses to install CCTV."*	P16	PC
C12	Golden-time overtrust failure risk	Process/ value	Over-reliance on AI in a genuine emergency risks missing the critical intervention window.	*"Overtrusting AI could mean missing the golden window in a real emergency."*	P4	PB
C13	Misinformation as worst case — no fact-checking	In vivo	Worst-case: AI provides wrong health information without checking, leading to harm.	*"Worst case: giving wrong information without fact-checking — like ChatGPT."*	P10	PB

Cluster D: Control, Agency, and Governance Architecture (11 codes)						
Code	Label	Type	Definition	Quotes	Participants	Pattern
D1	Elder as primary stakeholder — higher governance stake	Process/ value	Elder, as directly affected party, holds greater governance share than adult child.	*"Together — but parents holding the greater control. They are the ones affected."*	P6, P8, P10	PD
D2	Split governance: elder = user; child = financial authority	Process/ value	Elder interacts with platform; adult child controls payments and scheduling.	*"Parents use it — children control the billing and health appointment decisions."*	P7	PD
D3	Graduated control — child configures; elder self-manages	Process/ value	Child-led initial setup followed by progressive handoff to elder autonomous control.	*"Mainly me at first, then handing control to my parents to manage on their own."*	P15	PD
D4	Won't use if misuse is structurally possible	In vivo	Orthopedic risk-first reasoning: categorical non-adoption if any pathway to misuse exists.	*"If it can be misused, I won't use it."*	P9	PH
D5	Success = family communication preserved and enhanced	Process/ value	Platform succeeds only if it guides rather than replaces family communication.	*"Success means family communication is preserved and guided — not replaced."*	P8	PE
D6	Mutual intergenerational care — 100-year lifespan design	Process/ value	Design should support mutual care across both generations, not one-directional elder monitoring.	*"In an era of 100-year lifespans, focus on mutual intergenerational care."*	P7	PD
D7	Bidirectional sharing — children's lives shared with parents	Process/ value	If children's daily pressures were visible to parents, infrequent contact would be understood.	*"If parents could see how demanding our lives are, they'd understand."*	P7	PF
D8	Reverse-direction design — AI reminds children to call	In vivo	Platform logic should prompt adult children's relational behavior, not only monitor elders.	*"A reminder feature for the younger generation to call their parents."*	P16	PF
D9	Offline-first family culture — AI as human meeting trigger	In vivo	For highly offline families, AI's highest value is triggering real-world connection.	*"I hope it will remind us to meet more often — not replace the meeting."*	P16	PE
D10	Elder already using ChatGPT — AI not uniformly alien	Descriptive	Challenges assumption of uniform elder AI resistance: P6's parent already uses ChatGPT.	*"Dad uses ChatGPT already — he'd use this without hesitation."*	P6	PE
D11	AI-mediated health topics strengthen family communication	Process/ value	Health-related AI topics can organically catalyze family communication.	*"Relevant health topics can organically strengthen family communication."*	P9	PE

Cluster E: Adult Child as Digital Mediator and Gatekeeper (10 codes)						
Code	Label	Type	Definition	Quotes	Participants	Pattern
E1	Tech mediation as ongoing care practice	Descriptive	Digital help is embedded in regular caregiving — continuous, organic, and expected.	*"All the time — the Boomer generation is not comfortable with electronics."*	P6, P11	PD
E2	Responsibility felt acutely when introducing tech	Process/ value	Strong personal sense of responsibility for introducing technology and ensuring effective use.	*"Yes — very much so. Making sure they know how to use it adequately."*	P2, P7, P11, P12, P14, P15	PD
E3	Child as quality gatekeeper — withholds until satisfied	Process/ value	Adult child actively filters which solutions reach parents; applies professional quality standards.	*"I have never recommended a digital solution until I've vetted it myself."*	P11, P15	PD

E4	Language barrier as mediation limit — diaspora-specific	Descriptive	Language gaps constrain tech mediation effectiveness for diaspora families.	*"Language barriers make tech mediation for immigrant parents very challenging."*	P11, P13	PG
E5	Tech gift-giving as mediation form	Descriptive	Orthopedic doctor occasionally gives parents technology as gifts — mediation through procurement.	*"Occasionally — I give parents tech gifts like a smartwatch."*	P9	PD
E6	Never helped with tech — mediation gap	Descriptive	Financial consultant has never helped parents with technology — revealing the full mediation-absence end of spectrum.	*"I have never helped my parents with technology."*	P10	PD
E7	Distance-forced remote setup — diaspora child initiates	Descriptive	Geographic distance makes child-initiated technology setup the only viable adoption pathway.	*"I set up the Google Home device for them remotely — no choice."*	P12, P13, P16	PG
E8	Elder vulnerability to AI manipulation and scams	Descriptive	Children perceive parents as specifically vulnerable to AI manipulation and social engineering.	*"Boomer generation is easily scammed or fooled by AI."*	P11	PC
E9	Elder resistance to change — adoption needs child push	Process/ value	Elders resistant to change; adoption depends on adult child actively pushing the platform.	*"They probably won't use it unless I make them — they prefer the old ways."*	P13, P16	PD
E10	Workplace colleagues as co-mediators	Descriptive	Technology mediation is not exclusively the child's role — workplace networks co-scaffold elder digital capability.	*"Colleagues at work help them more closely on a daily basis."*	P16	PD

Cluster F: Design Expectations — Restraint, Warmth and Functional Specificity (18 codes)

Code	Label	Type	Definition	Quotes	Participants	Pattern
F1	Fewer features — minimalist one-click elder design	Descriptive	Elders need fewer features and one-click operation; simplicity is a dignity principle.	*"Comfortable for parents. Fewer features □ one-click health management."*	P2, P3, P4, P14	PF
F2	Warm non-technical AI tone	In vivo	AI should address elders in a warm, non-clinical register; not stiff or robotic.	*"Warm tone toward parents. Not stiff AI voice □ technology that feels safe."*	P5, P8	PF
F3	Customizable trusted human-facing avatar	Process/ value	Allowing elders to choose a trusted face, voice, and aesthetic increases emotional accessibility.	*"Let them choose the face, voice, and appearance □ builds emotional access."*	P6	PF
F4	AI as confidential emotional companion for undisclosed elder concerns	In vivo	AI provides a non-judgmental space for elders to disclose privately. Analytically novel: inverts platform logic from adult-child oversight to elder-initiated confidentiality.	*"A conversation partner that receives what elders won't tell children. Comfortable."*	P10	PF
F5	Conversational AI discomfort — prefer functional over social	Process/ value	Multiple participants reject expressive conversational AI; prefer transactional, data-first interactions.	*"Friend-like AI conversation feels uncomfortable — just give me the bio data."*	P3, P16	PF
F6	Administrative task coordination as primary utility	Descriptive	Appointment reminders, medication reminders, scheduling — lowest-risk, highest-utility functions.	*"Reminders, medication alerts, and admin coordination — most realistic value."*	P4, P7, P14, P15	PF

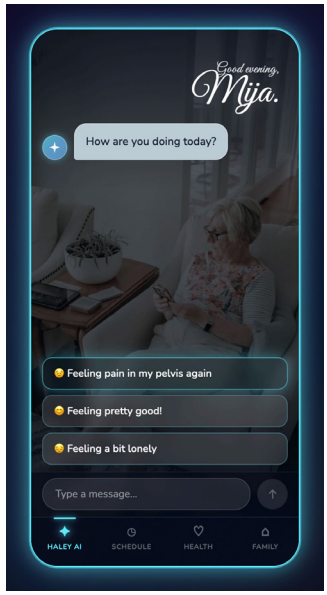
F7	Biometric passive monitoring preferred over conversation	Process/ value	Passive data collection preferred: less intrusive, more factual, harder to misinterpret.	*"I just want it to gather my bio data — pulse, weight, fall detection."*	P9, P16	PF
F8	Medication duplication detection — ENT clinical insight	Descriptive	Checking for duplicate prescriptions across multiple providers is the ENT's top design priority.	*"Duplicate medication checking across providers — ENT patient safety priority."*	P1	PH
F9	Sleep, exercise, and nutrition quality monitoring	Process/ value	Private education professional's holistic design vision: extend scope from illness to positive health.	*"Sleep goals, exercise targets, and food quality — not just illness monitoring."*	P3	PF
F10	Gamified shared family wellness challenges	Process/ value	Wellness professional's behavioral design lens: family exercise challenges build shared engagement.	*"Family exercise challenges with achievement messages — motivating together."*	P5	PF
F11	Family alignment and communication as core design goal	Process/ value	Family coordination is the primary design goal; individual monitoring is secondary.	*"The biggest first hurdle is internal family communications — not monitoring."*	P11	PF
F12	Multilingual and cultural accessibility as non-negotiable	Descriptive	Language accessibility determines which diaspora families can access the platform at all.	*"Multiple language support — help people where English is a second language."*	P11, P13	PG
F13	Quick access to information when needed — immediate utility	Process/ value	Orthopedic professional values speed and accuracy: platform most valuable when quick, reliable information is needed.	*"Most helpful when quick, reliable information is urgently needed."*	P9	PH
F14	Dual-user interface — elder and caregiver as co-users	Descriptive	Both elder and adult child need accessible, functionally distinct interface layers.	*"Both parents and children need their own accessible, functional view."*	P7, P8	PF
F15	AI as specialist triage gateway — not final authority	Process/ value	AI should route users to human clinical expertise; never serve as the final health authority.	*"If AI can connect to a human specialist for a second layer — that's the right model."*	P11	PB
F16	Reverse-direction — AI reminds children to contact parents	In vivo	Design logic should run bidirectionally: prompting children's relational behavior.	*"A reminder for the younger generation to call their parents."*	P16	PF
F17	Inclusive design for isolated elders beyond nuclear family	Process/ value	Platform should extend to socially isolated elders who entirely lack family support.	"Should reach isolated elders who have no family □ they need it most."	P8	PF
F18	Helpful if used within appropriate limits	Process/ value	Financial consultant's risk-controlled adoption philosophy: utility within defined boundaries.	"Useful when used within appropriate boundaries — within those limits, yes."	P10	PF

Note: PA = Monitoring as relational reassurance signal; PB = Trust as conditional, professionally mediated, multi-domain; PC = Surveillance-dignity boundary; PD = Adult children as gatekeepers; PE = AI as relational complement; PF = Design for minimum viable intervention; PG = Diaspora distance as a structural driver; PH = Health professionals as clinical validation authority.

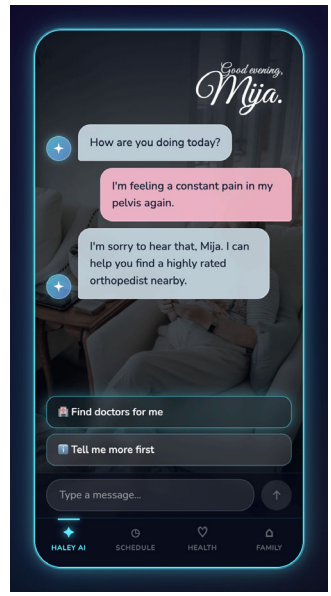
Appendix 2 Invisible AI Health Platform Features Refined Through Participatory Design Interview Sessions (N = 16)

Service feature	Participant Evaluation	Illustrative Quotation	Design Refinement
Administrative coordination	Participants prioritized practical support such as reminders, scheduling, and refill management over complex AI functions	"appointment reminders, medication reminders, refill reminders"	Position the platform as a low-risk coordination tool in daily care
Passive health monitoring	Participants preferred factual monitoring of health indicators rather than emotionally expressive AI interaction	"I just want some platform to gather my bio data and tell me anything is wrong."	Emphasize passive data capture and exception-based alerts
Low-burden interaction	Participants wanted fewer features, intuitive navigation, and elder-friendly access	"one-click" use	Reduce complexity and design for quick, accessible interaction
Clinically grounded safety support	Participants valued specific, verifiable health functions rather than abstract intelligence	"a function that checks duplicate medication use"	Include narrow, high-trust features with clear practical value
Human backup and verification	Participants did not want AI to operate as a final authority without escalation	"a human specialist to be vetted for a second layer or round"	Design AI as a triage or support layer, not a standalone decision-maker
Non-anthropomorphic interaction	Participants resisted conversational or companion-like AI when it felt artificial or intrusive	"friend-like AI conversation"	Avoid over-socialized AI and maintain a neutral, professional tone
Shared family coordination	Participants reframed the platform as a tool for coordinating care across family members, not only monitoring elders	"a reminder feature for the younger generation to call their parents"	Support bidirectional reminders and family-linked use cases
Multilingual and inclusive access	Participants highlighted linguistic and cultural barriers in family care, especially across distance	"multiple language support"	Design for multilingual access and culturally flexible onboarding

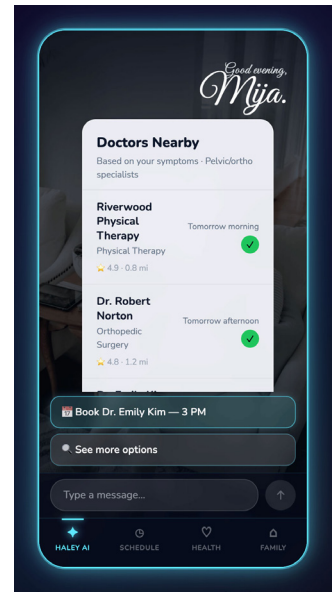
Note: This table summarizes the main service features refined through the participatory design interview sessions. The refinements show how participants moved the invisible AI health platform concept away from a generic AI health assistant and toward a more bounded, practical, and family-coordinated infrastructure model.



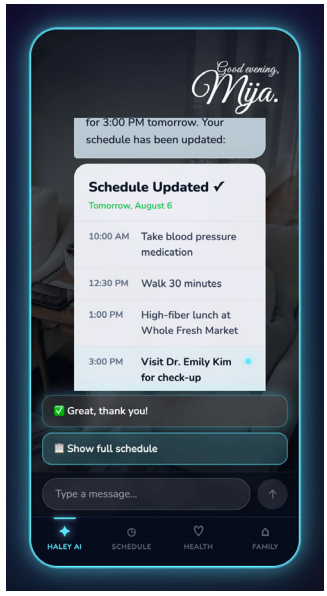
S1. Daily emotional check–in with response options



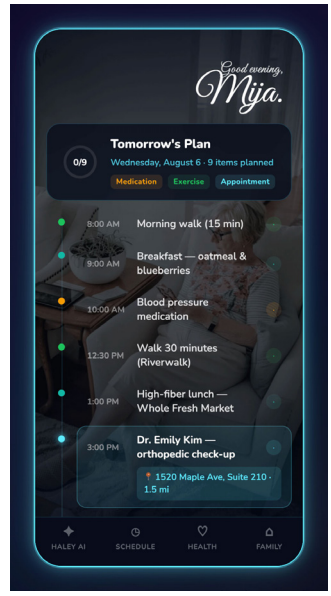
S2. AI response to reported pelvic pain, with an offer to locate appropriate care



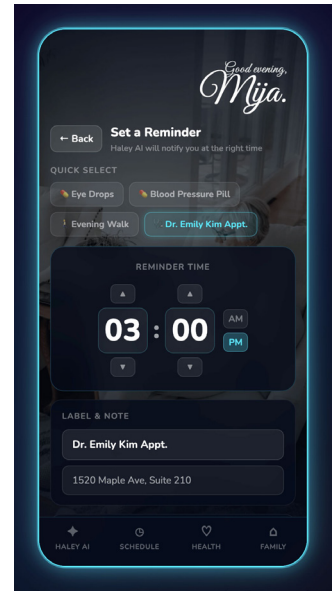
S3. Presentation of nearby providers and appointment–booking options



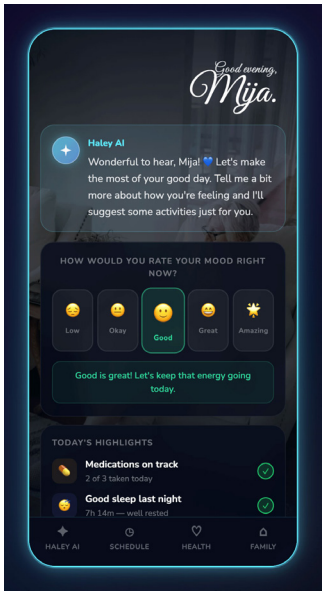
S4. Automatic schedule update following appointment selection



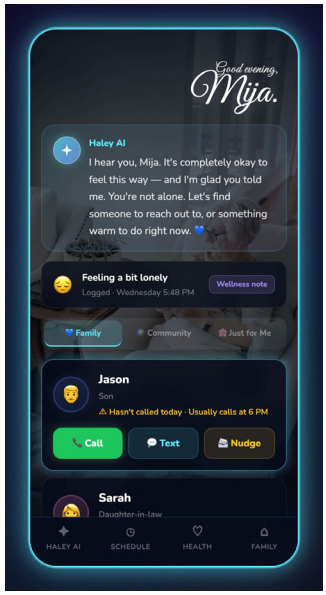
S5. Integrated daily plan covering medication, activity, meals, and care



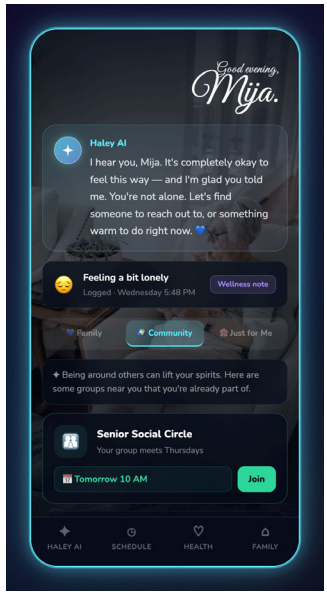
S6. User–configured medication, activity, or appointment reminder



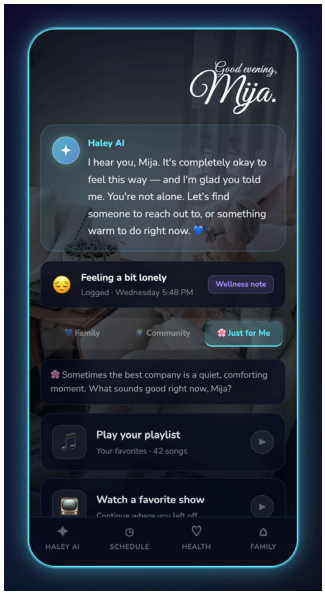
S7. Mood rating followed by encouraging feedback and daily highlights



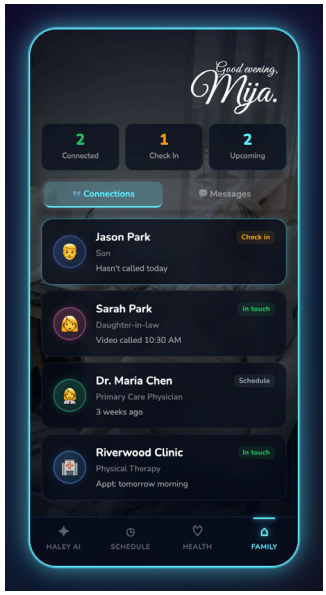
S8. Response to loneliness linked to patterns of family contact



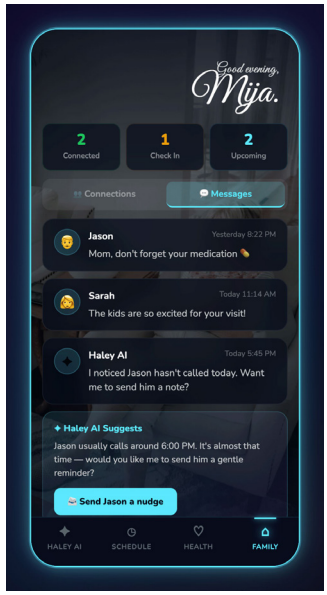
S9. Community–activity suggestion following disclosure of loneliness



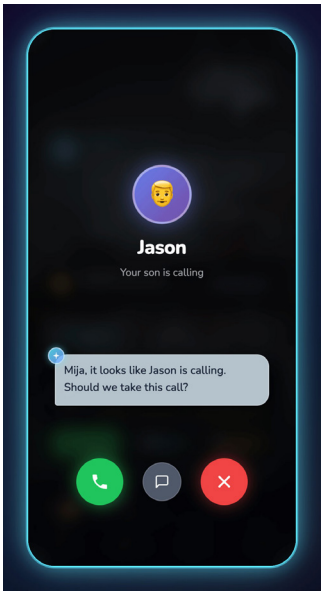
S10. Private self–soothing activities suggested following disclosure of loneliness



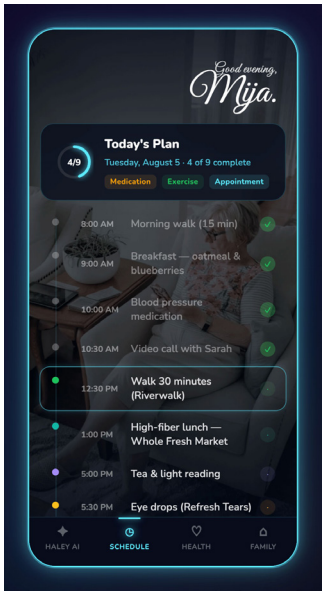
S11. Dashboard connecting the older adult with family members and clinicians



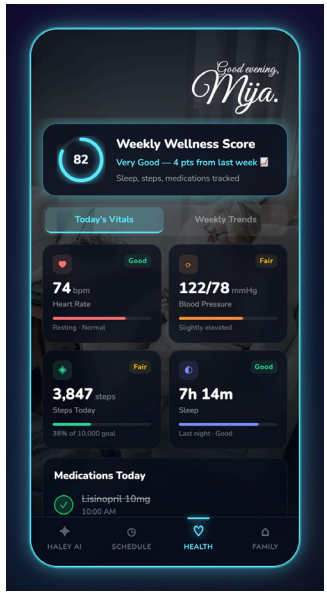
S12. Message history accompanied by AI–generated suggestions to contact a family member



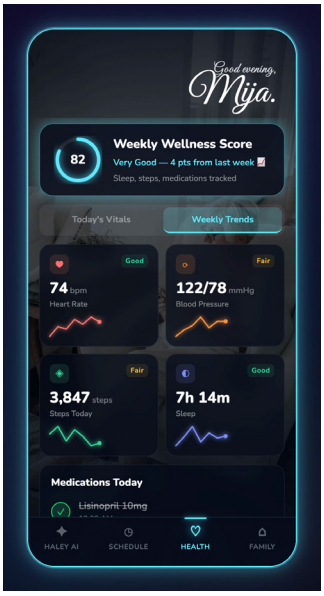
S13. AI–mediated notification of an incoming call from an adult child



S14. Progress display showing completed and upcoming daily activities



S15. Wellness score accompanied by current health indicators



S16. Weekly trends in vital signs, activity, sleep, and medication adherence

Appendix 4 Standardized Reporting Version of the Interview Protocol

Domain	No	Interview Prompt
Family context and caregiving involvement	1–1	How are your parents doing these days? (Do they live on their own or with family? What does their daily routine look like?)
	1–2	How involved are you in your parents' health or wellbeing — emotionally, practically, or digitally?
	1–3	Have you ever helped your parents use technology, such as smartphones, health apps, or AI speakers? How was that experience for you? (Was it easy, challenging, or uncomfortable?)
	1–4	How do you usually talk about health or safety issues within your family? (For example, through calls, messages, in-person or family group chats?)
Initial perceptions, trust, and control	2–1	When you hear the term 'AI health platform,' what comes to mind?
	2–2	How would you feel if you had to install or manage an AI service that quietly supports your parents' health and safety?
	2–3	What factors would make such a system feel trustworthy for you and your parents?
	2–4	On the other hand, what aspects might make you feel uneasy or hesitant?
	2–5	Who do you think should have the main control or responsibility for the system — you, your parents, or both together?
Scenario-based evaluation	3–1	If this happened to your parents, how would you feel?
	3–2	Would you consider this feature helpful for your family or a bit intrusive?
	3–3	How do you think your parents would react to it?
	3–4	From your perspective, would this kind of system bring you peace of mind, or would it feel like an additional burden?
Caregiving responsibility, privacy, and relational effects	4–1	Do you feel a sense of responsibility when introducing or managing technology to help your parents stay independent?
	4–2	How do you balance your desire to protect your parents with the need to respect their privacy?
	4–3	If AI replaced some of your personal interaction or caregiving, would you feel distant or guilty — or perhaps relieved?
	4–4	How could this kind of AI health platform help strengthen your family's connection and communication?
	4–5	If something went wrong or the technology was misused, what would be the worst-case scenario for you? And what would the best-case scenario look like — something that feels ideal for your parents and your family?
Expected benefits and design suggestions	5–1	In what ways could an AI health platform like this give your parents a sense of safety, comfort, or connection?
	5–2	How might it help reduce your own stress or caregiving burden as their child?
	5–3	Considering both generations, what would make you say, "This platform really works well for our family"?
	5–4	If you could design this AI health platform yourself, what kind of features or personality would you give it?
	5–5	Finally, what message or advice would you like to share with designers or researchers creating AI health platform services for families like yours?

Note: The original interviews were semi-structured and follow-up wording was adapted to participants' responses. The prompts formalize the protocol domains reported in Section 3.3.2 so that future researchers can reproduce the elicitation logic without implying that every probe was delivered verbatim in identical wording.