2026 S.T. Yau High School Science Award (Asia)

Research Report

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Title of Research Report

Social Isolation or Digital Divide: The Impact on Macao Elderly's Willingness to Use AI Remote Health Monitoring Devices

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Social Isolation or Digital Divide: The Impact on Macao Elderly's Willingness to Use AI Remote Health Monitoring Devices

LI Yuhan, Shi Yuyao, Zhu Ziqing

Abstract

As Macao's population ages, AI-enabled remote health monitoring has been promoted as a way to ease the care burden on elderly-only households, yet actual uptake among older residents remains low. Drawing on a survey of 500 community-dwelling older adults collected in Macao between March and June 2024 and split into non-users (N = 221) and current users (N = 279), this paper examines within a unified cost–benefit framework whether social isolation or digital training matters more for their willingness to adopt such devices, and whether the classic technology-acceptance constructs of perceived usefulness and perceived ease of use still carry explanatory power. The main effect of social isolation on willingness is not significant, consistent with two opposing channels that largely cancel out; perceived usefulness and perceived ease of use likewise fail to predict willingness among non-users, while technology anxiety retains a negative association. The most distinctive finding is a sign reversal in the social isolation × training interaction: among non-users, isolated older adults who had attended training reported lower, not higher, willingness ($\beta = -1.110$, $p = 0.076$), whereas among current users training was associated with higher satisfaction, and this gain was largest for the more isolated ($\beta = +0.758$, $p = 0.043$). These results suggest that, for older adults who have not yet adopted the device, structural and support-related factors outweigh attitudinal evaluations, and that classroom training without follow-up home support can be counterproductive for the socially isolated. Training aimed at this group should therefore shift from one-off instruction toward sustained support that bridges the gap between supervised learning and independent use.

Keywords: Social isolation, Digital training, Technology acceptance model, AI remote health monitoring, Ordered logit

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Acknowledgement

This study began with a brief conversation during community volunteer work in Macao. An elderly man wearing a government-distributed health wristband told us, with a slight smile, that he simply wore it because he was afraid of breaking it and did not understand its functions. That exchange prompted the question behind this thesis: even when remote health-monitoring devices are freely available, what determines whether older adults actually use and benefit from them? We set out to examine willingness to adopt AI-enabled remote health monitoring among non-users and satisfaction among current users, focusing on social isolation, technology anxiety, perceived usefulness and ease of use, digital training, and health status.

We are deeply grateful to our supervisor, Ms. Xia Changlan, for her rigorous and patient guidance throughout the project. From shaping an everyday observation into a coherent research question, through theoretical-model construction and variable specification, to her careful review of data and writing, her oversight kept the work on track.

As a three-person team, we shared both responsibilities and decisions. Li Yuhan, as team leader, coordinated the project, managed questionnaire distribution and data collection, drafted the introduction and literature review, and oversaw the final revision. Shi Yuyao built, derived, and tested the theoretical model and produced the conceptual figures. Zhu Ziqing designed the questionnaire items, conducted the data analysis, and contributed to drafting and revising the introduction, literature review, and conclusion. Much of the model's final shape—particularly the integration of non-user adoption intention and user satisfaction within a single cost–benefit framework—emerged from repeated joint discussion, trial calculations, and simplification rather than from any single member.

We acknowledge the use of AI tools during the research process. Perplexity (Sonar) assisted with literature and policy-document retrieval; DeepSeek-V4-Pro, Doubao-Seed-2.1-Pro, and Grok 4.6 supported model discussion, theoretical reasoning, cross-checking of Stata outputs, and language refinement. All statistical analyses were conducted independently by the team in Stata; AI tools were used solely for interpretation, verification, and expression. No AI-generated content was incorporated without independent review. The team bears full responsibility for the study's design, analysis, and conclusions, and all AI interaction records are available as Supplementary Materials.

We thank our families for their patience and encouragement through the summer of fieldwork, revision, and writing. Above all, we thank each other—for the debates, the mistakes, and the willingness to rebuild together.

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We hereby declare that we

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2. perform the research work ourselves and thus truly understand the content of the work.
3. observe the common standard of academic integrity adopted by most journals and degree theses.
4. have declared all the assistance and contribution we have received from any personnel, agency, institution, etc. for the research work.
5. have truthfully disclosed all AI tool usage in the research report and obtained prior approval from supervising teachers. All supporting documentation has been submitted as required. We hereby affirm that no improper use of AI has occurred at any stage of the research process.
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We understand and agree that failure to honor the above commitments may lead to disqualification from the competition and/or removal of award, if applicable; that any unethical deeds, if found, will be disclosed to the school principal of the team member(s) and relevant parties if deemed necessary; and that the decision of YHSA(Asia) is final and no appeal will be accepted.

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Table of Contents

Abstract i

Acknowledgement ii

Commitments on Academic Honesty and Integrity iii

1. Chapter 1: Introduction 1

2. Chapter 2: Literature Review and Theoretical Framework 6

3. Chapter 3: Theoretical Model and Research Hypotheses 19

4. Chapter 4: Research Design and Methodology 26

5. Chapter 5: Empirical Results and Discussion 37

6. Chapter 6: Conclusion 56

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Chapter 1: Introduction

1.1 Research Background

In July 2026, Macao Radio reported that the Social Welfare Bureau and the Macao Federation of Trade Unions (MFTU) would jointly set up a carer support centre in the northern district, aiming to begin operation within the year to provide various forms of support for elderly-only households and carers. The report mentioned that carers may face physical and mental stress and emotional distress during long-term care, and frontline social workers usually conduct home visits first to understand the living environment of the elderly and their carers before providing emotional support and nursing knowledge. At the same time, organisations such as MFTU have already launched several smart health monitoring projects. According to the project organiser, about 1,350 elderly people have participated (subject to official project data).

However, in actual use, many elderly people and their carers remain hesitant about such technologies. A 2024 survey showed that although 90.8% of elderly respondents owned a smartphone, 76.8% said they "dare not try" using online functions, including health-related applications and remote monitoring interfaces (Macao Jing Lao Association, 2024). This suggests that the barrier to technology adoption is not simply "having a phone," but a behavioural threshold of "daring to use and being willing to use."

In Macao, population ageing is continuing to deepen. According to the Macao Statistics and Census Service (DSEC, 2021), the population aged 65 and above reached 105,200 in 2025, constituting 15.3% of the total population of 688,900. At the current trajectory, this proportion is projected to surpass 21.4% by 2029, at which point Macao will formally enter what demographers term a "super-aged society"

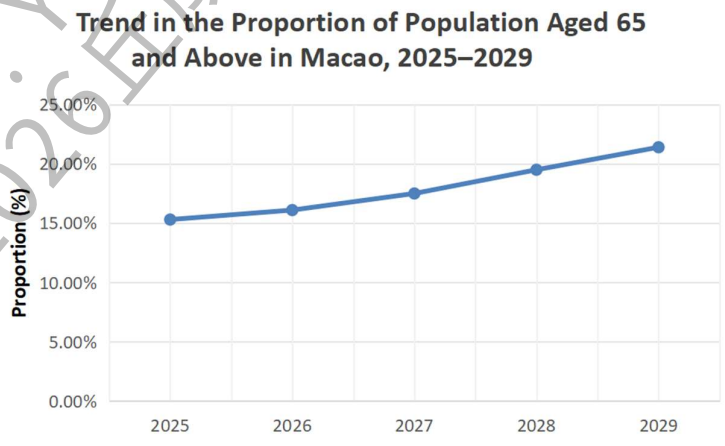


Figure 1.1. Trend in the Proportion of Population Aged 65 and Above in Macao, 2025–2029

Data source: Macao Statistics and Census Service (DSEC)

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This demographic change is also reflected in family care arrangements. The 2021 population census recorded 9,430 elderly individuals living alone and 10,290 elderly-only households.

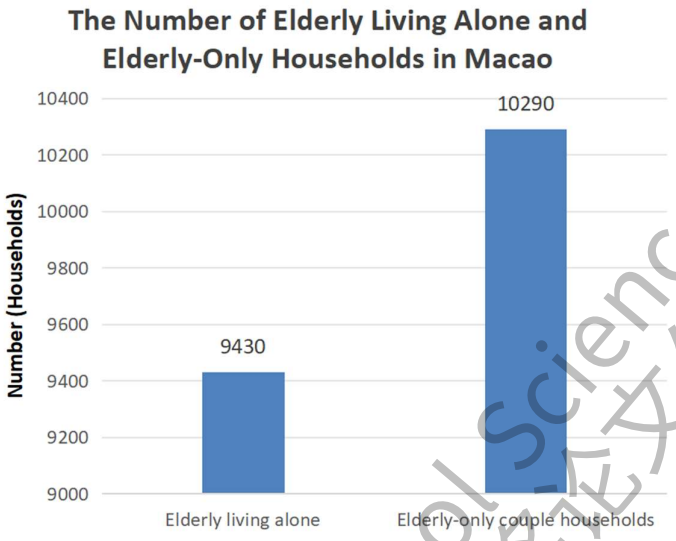


Figure 1.2. Number of Elderly Living Alone and Elderly-Only Households in Macao
Data source: 2021 Population Census, Macao Statistics and Census Service (DSEC)

As family sizes shrink and younger cohorts migrate for education or employment, the traditional multigenerational living arrangement that once served as the main source of care is weakening.

In terms of health, local data show that over 85% of elderly residents in Macao suffer from one or more chronic conditions, including hypertension, diabetes, and cardiovascular disease.

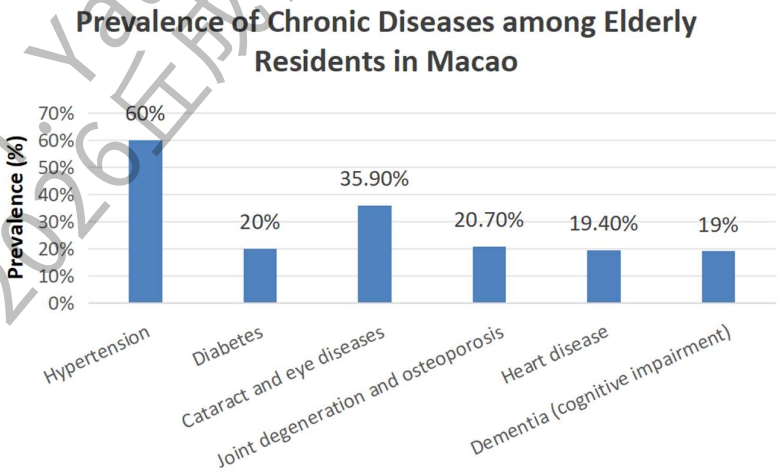


Figure 1.3. Prevalence of Chronic Diseases among Elderly Residents in Macao
Data source: Cheng Pou Daily News

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These conditions require sustained monitoring rather than episodic clinical intervention, which makes remote health monitoring technology more attractive.

It is against this backdrop that the Macao government and civil society organizations have turned to AI-enabled remote health monitoring. The Macao Federation of Trade Unions (MFTU), one of the territory's largest social service providers, launched a Smart Elderly Health Monitoring Program. The program deploys wearable devices and ambient sensors capable of tracking vital signs—heart rate, blood pressure, blood oxygen saturation, and sleep patterns—and transmitting these data to a cloud-based platform accessible to family members and community health workers $\beta 6(Si \times Ti)$.

However, the promise of AI-enabled health monitoring has only been partially realised. On the one hand, population ageing and the high prevalence of chronic diseases imply considerable potential demand. On the other hand, in reality, many elderly people—even those who have phones and devices—do not use these functions on a large scale. From existing discussions, whether elderly people are willing to use these devices may be related to whether they have someone to use them with, whether they have help, whether they dare to try, and how they view risk and uncertainty.

Macao's unique characteristics—its compact geography, its relatively concentrated elderly service ecosystem, and the availability of project-level participation data from MFTU and other initiatives—make it a suitable site for such an investigation. This study uses a newly collected dataset of 500 survey responses from Macao elderly residents to look at which of the following matters more for elderly people's willingness to use these devices: social isolation, smartphone ownership and digital training, risk attitudes, or perceived usefulness and ease of use.

1.2 Research Questions and Objectives

This study mainly asks: in Macao, which factors matter more for elderly people's willingness to use AI remote health monitoring devices—social isolation or digital conditions (proxied by digital training)? After controlling for these factors, do perceived usefulness and perceived ease of use still matter?

Smartphone ownership is treated only as background information. Given the already very high penetration rate among Macao older adults, it is not included as a core explanatory variable in the empirical models; digital training is used instead as the main proxy for digital conditions.

Risk attitudes are discussed as theoretical background inspired by prospect theory, but are not retained in the final empirical equations.

This question decomposes into three interrelated sub-questions.

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First, to what extent does the degree of social isolation predict willingness to adopt AI health monitoring technology among elderly Macao residents? This directly tests the digital divide hypothesis against its rival.

Second, after controlling for social isolation, does digital training (the primary proxy for digital-access conditions) still have statistically and economically significant effects on adoption willingness? Risk-attitude considerations derived from prospect theory are explored theoretically but not tested empirically. This probes the mechanisms beyond the social-versus-demand dichotomy.

Third, do the standard TAM constructs of perceived usefulness and perceived ease of use retain explanatory power in this context, or are their effects superseded by structural and behavioural variables? This provides a test of TAM's applicability to the local elderly population.

Based on the above questions, the objectives of this study can be summarised as follows:

- Theoretically, drawing on the Technology Acceptance Model (TAM) and prospect-theoretic reasoning about risk attitudes, this study uses a Macao elderly sample to examine how social-context and attitudinal variables (perceived usefulness, perceived ease of use, technology anxiety and digital training) jointly shape adoption willingness. Prospect-theory-derived risk-attitude arguments serve only as conceptual background rather than empirical test targets.

- Empirically, using 500 Macao elderly survey responses, this study estimates a logit probability model to test the actual associations between social isolation, digital training, technology-related attitudes, and adoption willingness.

- Practically, based on the empirical results, this study provides a reference for community service organisations and relevant projects when designing training, outreach, and device allocation—for example, whether resources are better placed on improving device accessibility and digital training, or on dividing target groups by living arrangements or risk attitudes.

1.3 Research Significance

This study has certain reference value at the theoretical level and at the individual and community levels.

Theoretical level

At the theoretical level, drawing on the Technology Acceptance Model (TAM) and prospect-theoretic reasoning regarding risk attitudes, this study uses a Macao elderly sample to provide supplementary empirical observations on how social-context and attitudinal constructs jointly shape older adults' adoption willingness toward AI-enabled remote health-monitoring

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devices. Prospect-theory-derived risk-attitude arguments serve as conceptual background rather than empirical test targets.

Individual and community level

At the individual level, the findings can help elderly people and their families better understand the factors affecting willingness to use these technologies—for example, whether social contact, device accessibility, or views on risk matter more.

At the community level, the findings can provide a reference for community service organisations such as MFTU and relevant projects when designing training, outreach, and device allocation. If the empirical results show that digital access (such as smartphone ownership and digital training) has a larger effect on willingness than social isolation, then resources may be better placed on improving device accessibility and digital literacy. Conversely, if social isolation has a stronger effect, then interventions targeting the reconstruction of social networks and peer support may be more needed.

Policy level (brief)

At the policy level, as Macao advances its "Smart City" initiative under the broader regional development framework, integrating AI-driven health services into community-based eldercare has become an important direction. The micro-level evidence provided by this study can offer local data support for the design and evaluation of future related projects, helping to reduce the risk of resource misallocation.

1.4 Paper Structure

The remainder of this paper is organised as follows:

- Chapter 2 Literature Review and Theoretical Framework

reviews literature on technology acceptance, social isolation and digital divides, and behavioural-economic models of health decision-making, and constructs the theoretical framework of this study.

- Chapter 3 Theoretical Model and Research Hypotheses

develops the theoretical model by combining the CRRA utility function with prospect theory's value function, derives a logit-form adoption probability, and proposes four testable hypotheses.

- Chapter 4 Data and Methods

describes the survey instrument, sampling strategy, and variable construction from 500 Macao elderly respondents, and details the econometric methodology.

- Chapter 5 Empirical Results and User Experience

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presents baseline logit regressions, average marginal effects, heterogeneity analysis, robustness checks, and a descriptive account of user experience and satisfaction among current adopters.

- Chapter 6 Conclusion

summarises the findings, offers policy recommendations, points out directions for future research, and notes the limitations of this study.

Chapter 2: Literature Review and Theoretical Framework

2.1 The Technology Acceptance Model and Elderly Use of Smart Devices

The Technology Acceptance Model (TAM), developed by Davis (1989), is a classic framework for explaining why people accept or reject information technology. The model identifies perceived usefulness (PU) and perceived ease of use (PEOU) as the two core factors influencing attitudes toward use and actual usage intention. Perceived usefulness refers to the degree to which a person believes that using a particular system would enhance his or her job or life performance; perceived ease of use refers to the degree to which a person believes that using the system would be free of effort (Davis, 1989).

The theoretical roots of TAM can be traced to the Theory of Reasoned Action (TRA). TRA posits that an individual's attitude toward a behaviour and subjective norms influence behavioural intention, which in turn influences actual behaviour (Fishbein & Ajzen, 1975). The Theory of Planned Behavior (TPB) further incorporates perceived behavioural control, indicating that individuals are more likely to form intentions and act when they believe they possess the necessary capabilities and resources (Ajzen, 1991).

Davis (1989) applied this behavioural-intention logic to the information-technology context. The basic path of TAM can be summarised as follows: external variables first shape users' judgements of usefulness and ease of use; PU and PEOU then influence attitude toward use and usage intention; usage intention is ultimately linked to actual use. PEOU may also exert an indirect effect on PU, because users who find a system easy to operate are more likely to perceive its functional value. In short, TAM does not merely ask whether a technology is good; it asks whether users believe it is helpful and whether they believe they can use it.

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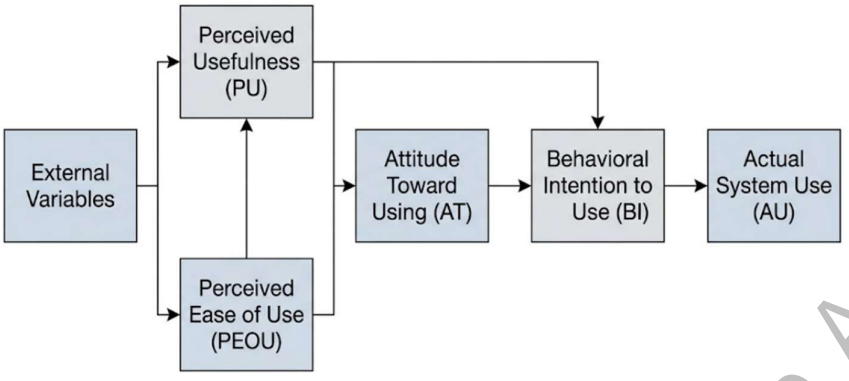


Figure 2.1. Basic Theoretical Path Diagram of TAM
Source: Self-drawn by the author.

Later research extended this framework. Venkatesh and Davis (2000) proposed TAM2, which added subjective norms, image, job relevance, output quality, and experience to the original TAM in order to explain why PU and usage intention vary with social context and personal experience. Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which synthesised multiple prior models and incorporated performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT2 further added hedonic motivation, price value, and habit for consumer contexts (Venkatesh et al., 2012).

These extensions demonstrate that while PU and PEOU remain central, technology adoption is not determined by attitudinal variables alone. Social influence, prior experience, practical resources, and facilitating conditions also shape whether users are willing to begin using a technology and whether they can sustain its use. For older adults, the availability of devices, guidance, repeated practice opportunities, and someone to turn to when problems arise is often as important as PU and PEOU themselves. This perspective aligns directly with the cost–benefit structure developed in Chapter 3, in which PU and PEOU enter the benefit function while support-related factors enter the cost function.

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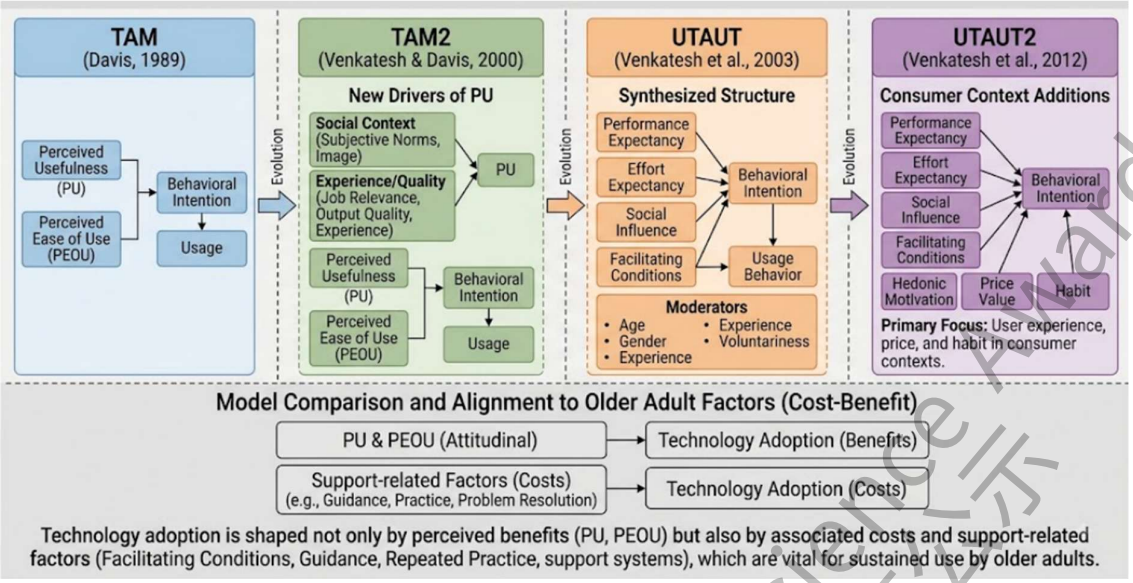


Figure 2.2. Evolution and Comparison of TAM to UTAUT2
Source: Self-drawn by the author.

Regarding measurement, Davis (1989) developed multi-item scales for PU and PEOU. In tests involving electronic mail and the XEDIT system, Cronbach's α for PU was 0.97 and for PEOU was 0.86 and 0.93; after sample pooling the coefficients were 0.97 and 0.91, respectively. The scales also demonstrated high convergent, discriminant, and factorial validity (Davis, 1989).

Subsequent studies adapted these constructs across office systems, web services, mobile technologies, and health technologies. Longitudinal work by Venkatesh and Davis (2000) showed that the effect of PU on usage intention is moderated by social influence and experience. A meta-analysis by Hauk et al. (2018) found that the relationship between chronological age and technology acceptance is not uniform; technology type, usage context, and user characteristics moderate the associations among PU, PEOU, and intention.

In the health-technology domain, TAM has been applied to patients' and older adults' acceptance of telemedicine, mobile health applications, electronic health records, and wearable devices. Systematic reviews indicate that perceived usefulness, perceived ease of use, trust, privacy concerns, technology anxiety, and social support are frequently identified as relevant factors, although findings vary by age group, clinical context, and device type (Peek et al., 2014; Hauk et al., 2018).

Studies focused on older adults show that the relative importance of PU and PEOU may differ from patterns observed among younger users. Chen and Chan (2011), in a review of technology acceptance among older adults, noted that the standard TAM remains useful but should incorporate age-related physical, psychological, and social factors. For many older adults, even when a device

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offers health monitoring or safety alerts, complicated operations, unclear interfaces, or fear of pressing the wrong button can still reduce willingness to use it (Chen & Chan, 2011; Mitzner et al., 2010).

Perceived ease of use among older adults typically reflects not only device design but also self-efficacy, prior experience, and the availability of support. Peek et al. (2014) concluded that older adults evaluating home-based technologies weigh benefits, operational burden, privacy, cost, personal need, and social influence simultaneously. Mitzner et al. (2010) likewise observed that older adults' attitudes are context-dependent: the same individual may willingly adopt a technology that solves a clear daily problem yet reject another whose learning cost is high or whose utility is unclear.

Help from family members, peers, health professionals, or community workers can also shape older adults' confidence in their ability to use a device. Wilson et al. (2022) noted that digital engagement can facilitate family contact, daily management, and service access for some older adults, yet barriers related to device accessibility, skills, support, and prior negative experiences persist. Technology adoption among older adults is therefore not solely an individual attitudinal issue; it is also conditioned by the presence or absence of support and learning opportunities.

In medical and health-technology settings the meaning of PU is usually more concrete. For the older adults in the present study, PU may encompass the ability to monitor one's health status in a timely manner, to notify family members or service providers in the event of abnormalities, to increase a sense of security, and to support more independent living at home. PEOU may encompass ease of learning, clarity of steps, readability of interfaces, ease of wearing or connecting the device, and the availability of help when problems arise.

When prior research has employed TAM scales, multiple Likert-type items are typically used to measure PU and PEOU separately, with subsequent checks of internal consistency, convergent validity, and discriminant validity. For older-adult and health-technology contexts, item wording must be concrete, readily comprehensible, and closely tied to actual operational scenarios. Chen and Chan (2011) emphasised that scales used with older adults should take physical capacity, cognitive load, prior experience, and social support into account. Accordingly, the present study employs the PU and PEOU constructs to examine older adults' basic evaluations of AI-enabled remote health-monitoring devices; specific questionnaire items, scale composition, reliability, validity, and operationalisation are detailed in Chapter 4.

Therefore, this study includes perceived usefulness and perceived ease of use in the subsequent analysis. For Macao older residents, whether a device is seen as "useful"—for example, whether it can help them keep track of their health and notify family members when something is abnormal—

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and whether it is seen as “easy to use”—for example, whether the steps are clear and easy to learn—may both be related to future adoption intention.These two constructs map directly onto the benefit function and Hypotheses H2 and H3 derived in Chapter 3.

It should be noted that the predictive power of the classic TAM constructs may be weaker among non-users who have no direct experience with the technology. For this group, perceptions of usefulness and ease of use are often formed on the basis of abstract imagination rather than concrete usage experience, which can attenuate the expected positive effects of PU and PEOU on adoption intention. This boundary condition is particularly relevant to the present study, which separately examines non-users and current users.

2.2 Social Isolation, Health Behaviour, and the Digital Divide

Social isolation can affect older adults’ health and daily life. Holt-Lunstad et al. (2015) showed in a meta-analysis that a lack of social connections is linked to higher mortality risk. Leigh-Hunt et al. (2017) also found that social isolation and loneliness are associated with various poor health outcomes.

Social isolation and loneliness are not identical. Social isolation typically refers to objectively limited contact with family, friends, or social networks, whereas loneliness emphasises the subjective perception that one’s social relationships are insufficient or unsatisfactory. The two may co-occur or appear independently (National Academies of Sciences, Engineering, and Medicine, 2020). The present study observes social isolation primarily through living arrangements and contact frequency, focusing on the daily contact and informal support available to older adults.

However, the effect of social isolation on health-technology adoption does not necessarily run in only one direction. From the perspective of the Selection, Optimization, and Compensation (SOC) model, older adults facing declines in physical capacity, resources, or social support may compensate for resource loss by learning new skills, seeking alternative tools, or mobilising formal and informal support (Baltes & Baltes, 1990). In the health-care context, remote monitoring devices can be viewed as a potential compensatory resource: when everyday care is insufficient, such devices may provide abnormality alerts, health information, and channels of contact with family or service providers.

Nevertheless, the availability of a compensatory technology does not guarantee that older adults will adopt it. The SOC model also emphasises that successful compensation ordinarily requires accessible resources, tools matched to individual capabilities, and external support. If a device is difficult to operate, if training is lacking, or if no one is available to assist, a technology that might otherwise serve a compensatory function may never enter older adults’ daily lives.

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But “higher need” does not automatically translate into higher use. Howe et al. (2023) found that during COVID-19 the most socially isolated older adults were significantly less likely to use telehealth, suggesting that higher need does not automatically translate into higher actual use when support and access barriers remain.

On the other hand, social isolation may also reduce technology use. Digital-divide theory points out that technology use depends not only on having a device, but also on whether there is someone to demonstrate, whether help is available, and whether there are chances to learn (Hargittai, 2002; Friemel, 2016; van Dijk, 2020). Older adults with fewer regular social contacts may receive less encouragement, fewer role models, and less practical assistance, and therefore find it harder to learn new devices.

The digital divide is commonly understood at three levels: access (device and network availability), use (skills, confidence, and actual operation), and outcomes (whether use yields health, informational, or social benefits) (Scheerder, van Deursen, & van Dijk, 2017). For older adults, improvements in access do not automatically close gaps at the use and outcome levels. Even older adults who own smartphones may still under-utilise health-related functions because of limited experience, fear of making mistakes, or the absence of someone to turn to for help.

Measurement of social isolation among older adults also rests on established instruments. The Lubben Social Network Scale (LSNS) and its abbreviated form LSNS-6 typically assess family and friend contacts, available support, and network size. Lubben et al. (2006), examining three European community-dwelling samples, reported high internal consistency (approximately $\alpha=0.83$), stable factor structures, and good convergent validity for the LSNS-6 and its family and friends subscales. Subsequent work has reported Cronbach’s α values in the range 0.83–0.86 (Lubben et al., 2006).

The present study does not adopt the full LSNS-6. Instead, it constructs a social-isolation index from questionnaire items on living arrangement and contact frequency, thereby capturing the daily contact and informal support available to respondents. The index shares with established scales a focus on family ties, social networks, and support conditions; it differs in relying on a simplified local proxy. Coding procedures, construction details, and limitations are presented in Chapter 4.

This forms the dual mechanism that this study focuses on. First, social isolation may deprive older adults of informal care and thereby increase the need for health monitoring, abnormality alerts, and a sense of security. Second, social isolation may reduce opportunities for technical demonstration, learning, and everyday assistance, thereby raising operational difficulty and technology anxiety. The two paths run in opposite directions, so the net relationship between social isolation and future adoption intention must be observed empirically. This dual mechanism corresponds exactly to the

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partial derivative $\partial Ui/\partial Si = -\beta 1 - \beta 6 Ti$ and to the non-directional Hypothesis H1 derived in Chapter 3.

Self-rated health is retained as a control variable in the empirical models.

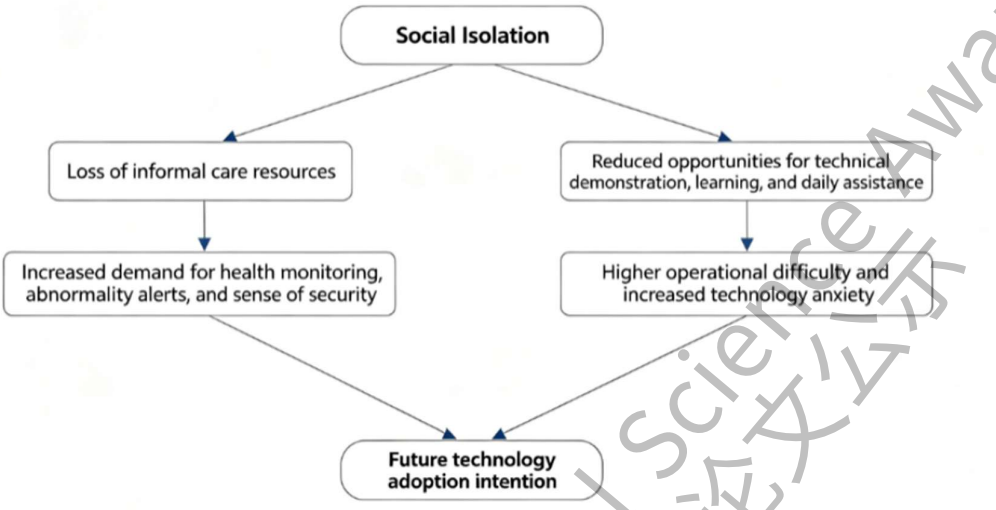


Figure 2.3. Dual Mechanism between Social Isolation and Future Adoption Intention
Source: Self-drawn by the author.

In the Macao context, a survey conducted by the Macao Jing Lao Association found that 90.8 % of older respondents owned a smartphone, yet 76.8 % reported that they “dare not try” online functions (Macao Jing Lao Association, 2024). This shows that owning a device does not mean people feel comfortable using health-related functions. Therefore, in addition to social isolation, this study also includes digital training in the analysis.

Digital training may serve as a substitute when social support is insufficient. For older adults who lack help from family or friends, training can provide demonstrations, learning opportunities, and channels for seeking help (Bhattacharjee et al., 2020), in a study of digital training programmes for community-dwelling older adults, found that one-to-one guidance, device support, and continued assistance helped increase digital participation.

The effectiveness of digital training may also vary with the older adult’s support environment. For those who continue to receive assistance from family or friends, problems that arise after training are more readily solved; for more isolated older adults, training may be one of the few available sources of technical support, yet its benefits may remain limited if no follow-up assistance is available after the training ends.

Therefore, this study further examines the interaction between social isolation and digital training. The theoretical rationale is that when older adults lack technical support from family or friends, training may supply a partial substitute; however, if training consists of only a short course and the

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older adult returns home without anyone to consult, the effect of training may be constrained. In other words, the association of digital training with adoption intention may differ according to the level of social support available. The interaction term is used to observe whether training attenuates—or fails fully to compensate for—the lack of digital support linked to social isolation. Because the present study relies on cross-sectional survey data, the analysis can only reflect associations among variables and cannot establish a causal effect of training. This interaction corresponds directly to the term $\beta 6(Si \times Ti)$ in the cost function of Chapter 3 and to Hypothesis H5.

Prior research on digital skills training for older adults has consistently emphasised the need for sustained support. Bhattacharjee, Baker, and Waycott (2020), reviewing studies of older adults' acquisition of digital skills, noted that learners frequently encounter difficulties related to memory, confidence, physical capacity, and lack of support; consequently, training format, pacing, and follow-up assistance shape learning experiences. Ahmad et al., (2022) likewise concluded in a systematic review that instructional strategies for older adults learning digital technologies should incorporate repeated practice, age-appropriate materials, and individualised support. These findings supply the theoretical basis for examining the social-isolation × digital-training interaction in the present study.

Regarding the measurement of digital training, prior studies typically record whether older adults have attended courses, the frequency and format of training, or changes in digital competence. Prior studies have examined the effects of home-based technology training combined with ongoing support. The present study uses participation in any community digital-literacy or technology-training programme within the past two years as a binary proxy for digital-support conditions; questionnaire design, coding, and limitations are detailed in Chapter 4.

Concerning smartphone ownership, although local data indicate that ownership rates among Macao older adults are already high, the final empirical models in Chapters 3–5 do not treat smartphone ownership as a core explanatory variable. Its influence is likely to be partially absorbed by perceived ease of use, digital training, and other digital-support conditions. Smartphone ownership is therefore discussed in this chapter only as background information on digital accessibility and is not retained as a core variable in the empirical specification.

Direct empirical evidence on Macao older adults remains limited. This study will use local survey data to observe the association between social isolation and future adoption intention after controlling for digital training and other related factors.

2.3 Prospect Theory and Risk Attitudes in Health Decision-Making

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When deciding whether to adopt a health-monitoring device, older adults need to weigh possible benefits against possible concerns. The device may help them detect health changes earlier and notify family members when something is abnormal. At the same time, learning to operate it, worrying about privacy, fearing pressing the wrong button, or worrying about device failure can create concerns.

Kahneman and Tversky (1979) proposed prospect theory, which points out that people usually evaluate changes relative to the status quo and tend to be more sensitive to losses than to equivalent gains. Tversky and Kahneman (1992) further showed that when facing uncertain outcomes, people may assign different psychological weights to certainty, safety, and potential losses.

Prospect theory has been applied to a range of health decisions, including cancer screening, vaccination, treatment choice, and risk communication. Research indicates that the framing of health information can alter judgements about screening, prevention, and treatment; describing outcomes as “avoiding a loss” versus “obtaining a gain” may elicit different behavioural responses (Rothman & Salovey, 1997; Gallagher & Updegraff, 2012).

A common feature of health decisions is that potential benefits often lie in the future and are uncertain, whereas costs—learning effort, expense, anxiety, or privacy concerns—may be incurred immediately. Consequently, individual attitudes toward certainty and loss can influence willingness to accept a new health service or device. For older adults, a health-monitoring device may be construed either as a tool that reduces the risk of undetected emergencies or as a source of learning burden, privacy concern, or operational pressure.

In the health-monitoring setting, older adults may see “having no device and no one knowing when something goes wrong” as a potential risk, or they may see “having to learn new operations, worrying about data leakage, or worrying about operating errors” as another kind of loss. Therefore, even if they recognise the health value of the device, they may still be unwilling to try it because of concerns about operational risk or learning costs.

Risk-attitude research commonly employs experimental choice tasks, risk questions, or multiple lottery choices to observe preferences for certain versus uncertain outcomes. Holt and Laury (2002) used a multiple-price-list method to measure risk aversion; Dohmen et al. (2011) compared experimental choices with self-reported risk attitudes and concluded that simple questions can supply useful information on risk preference but cannot replace full structural-parameter estimation.

This study constructs a “risk-averse choice tendency” from the choice questions Q29–Q33. This variable reflects whether respondents prefer certain outcomes or uncertain outcomes in several hypothetical choices. It serves as a survey proxy for risk attitude. It is not equivalent to the loss-

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aversion parameter λ in prospect theory, nor is it used to estimate individual-level CRRA parameters. Because the final empirical models in Chapters 3–5 do not treat this variable as a core predictor, the present study regards it solely as theoretical background and supplementary information for understanding risk attitudes, not as a primary empirical conclusion.

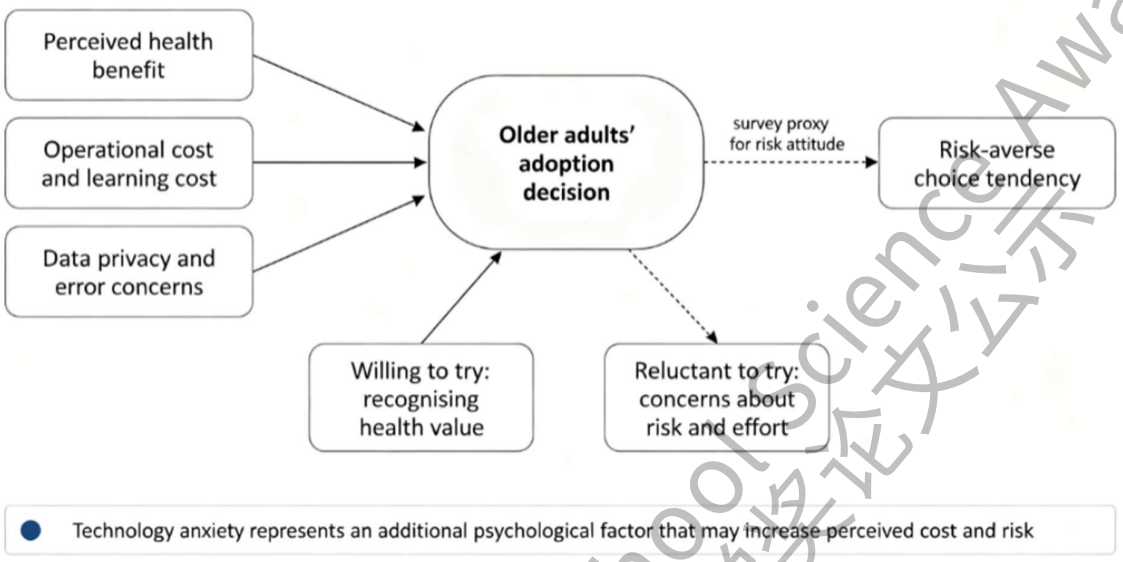


Figure 2.4. Cost, Benefit, and Risk Considerations in Health Monitoring Device Adoption
Source: Self-drawn by the author.

Technology anxiety is another psychological factor that needs attention. Technology anxiety refers to the tension, worry, or helplessness that people feel when facing smart devices—for example, worrying that they cannot learn, fearing operating errors, or not knowing what to do when the device fails. Related studies show that technology anxiety can reduce willingness to use self-service technologies and digital services (Rosen & Weil, 1995; Brosnan, 1998; Meuter, Ostrom, Bitner, & Roundtree, 2003).

Technology anxiety has also received sustained attention in research on older adults' technology adoption. Czaja et al. (2006), reporting findings from the CREATE project, found that age, education, cognitive ability, and prior computer experience are all related to technology use; limited experience and lower self-efficacy can increase difficulties. Chen and Chan (2011) likewise identified anxiety, lack of confidence, and operational burden as important factors affecting older adults' technology acceptance.

Several instruments exist for measuring technology anxiety. The Computer Anxiety Rating Scale (CARS), for example, assesses discomfort and anxiety when facing computers, while the Technology Readiness Index (TRI) captures optimism, innovativeness, discomfort, and insecurity toward new technologies. Parasuraman (2000) reported internal-consistency coefficients of

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approximately 0.74–0.81 for the four TRI dimensions, indicating that the instrument can distinguish facilitating from inhibiting psychological orientations toward technology.

Therefore, this study observes technology anxiety separately from perceived ease of use. Perceived ease of use mainly reflects whether older adults think the device is easy to learn and operate; technology anxiety reflects whether they feel tense, afraid, or helpless when facing the device. The two may be related, but they are not the same. Prior research typically treats PU, PEOU, and technology anxiety as separately measurable constructs. PU and PEOU primarily capture cognitive evaluations of functional value and operational difficulty, whereas technology anxiety captures affective responses of tension, fear, helplessness, or insecurity. Davis (1989) demonstrated discriminant validity between PU and PEOU through multitrait–multimethod analysis; Parasuraman (2000) likewise treated technological discomfort and insecurity as dimensions distinct from judgements of technology utility. Although "finding a device difficult" and "feeling afraid of it" may correlate, they are not identical.

In the subsequent empirical models, technology anxiety ($TAnx$) enters as an independent cost-side predictor corresponding to the term $\beta 4 TAnxi$ in the cost function of Chapter 3 and to Hypothesis H4. Perceived usefulness and perceived ease of use are related to the technology-acceptance composite index ($TAcc$). $TAcc$ is formed by averaging the six PU and PEOU items and serves as an auxiliary attitudinal control that is introduced in Model 3 and retained in Model 4; it is not equivalent to the anxiety parameter in the theoretical cost function. Variable construction and measurement details are provided in Chapter 4.

The constant-relative-risk-aversion (CRRA) framework can help illustrate that different individuals may place different weight on health uncertainty (Mas-Colell, Whinston, & Green, 1995). This study only uses CRRA and prospect theory as a theoretical background for understanding risk attitudes; it does not estimate specific structural parameters.

Although prospect theory and individual risk attitudes provide important theoretical insights into how older adults may weigh potential losses against potential gains when deciding whether to adopt a health-monitoring device, the present study treats risk attitudes solely as theoretical background. The survey items designed to capture risk-averse choice tendency (Q29–Q33) are not included in the final empirical models of Chapters 3–5. The empirical focus is placed on social isolation, digital training, technology anxiety, and the TAM constructs.

2.4 Literature Commentary and the Position of This Study

Existing studies have discussed related issues from three angles: the Technology Acceptance Model, social isolation and the digital divide, and risk attitudes in prospect theory. TAM

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emphasises perceived usefulness and perceived ease of use; research on social isolation and the digital divide emphasises family support, information access, and learning opportunities; prospect theory suggests that people may make different choices because they fear losses, prefer certainty, or worry about risks.

From the existing literature at least three issues warrant further observation. First, while TAM has been widely used to explain technology adoption, older adults' use of health devices may also be shaped by social support, health status, and technology anxiety. Second, social isolation may simultaneously increase the need for health monitoring and reduce technical support, so its net direction is theoretically indeterminate. Third, digital training may supply compensatory help for older adults who lack family-based technical support, yet whether training is sufficient to alter the relationship between social isolation and adoption intention remains an empirical question. These observations map directly onto the net-utility index $Ui = ln\ Bi - ln\ Ci$ and Hypotheses H1–H5 derived in Chapter 3.

In addition, existing research has often examined "adoption intention" and "actual use" separately. Adoption intention reflects willingness to begin trying a technology; actual-use experience concerns operational ease, availability of support, difficulties encountered, and willingness to continue. For older adults' health technologies these two stages may share some common determinants yet also differ. Observing both future adoption intention among non-users and use experience among current users therefore helps illuminate possible gaps between "wanting to use" and "being able to sustain use."

Building on existing research, this study uses local Macao survey data to examine the associations of social isolation, perceived usefulness, perceived ease of use, technology anxiety ($TAnx$), digital training, and the social-isolation × digital-training interaction with future adoption intention, while also incorporating the technology-acceptance composite ($TAcc$) and demographic and health controls, including self-rated health. The role of social isolation is of particular interest: it may increase the need for health monitoring, or it may lower usage intention because of a lack of technical support.

This study also distinguishes two observation levels: future adoption intention and actual use experience. For older adults who have not used the device, the study focuses on whether they are willing to try it under free or heavily subsidised conditions. For those who have already used the device, the study adds observations on use difficulties, sources of help, and satisfaction. These two groups are not treated as a single homogeneous sample; rather, the analysis separately examines the stage of "willingness to begin use" and the stage of "ability to sustain use after adoption." The user-

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experience component supplies a supplementary check on whether the cost–benefit and technical-support mechanisms remain relevant once the device is actually in use.

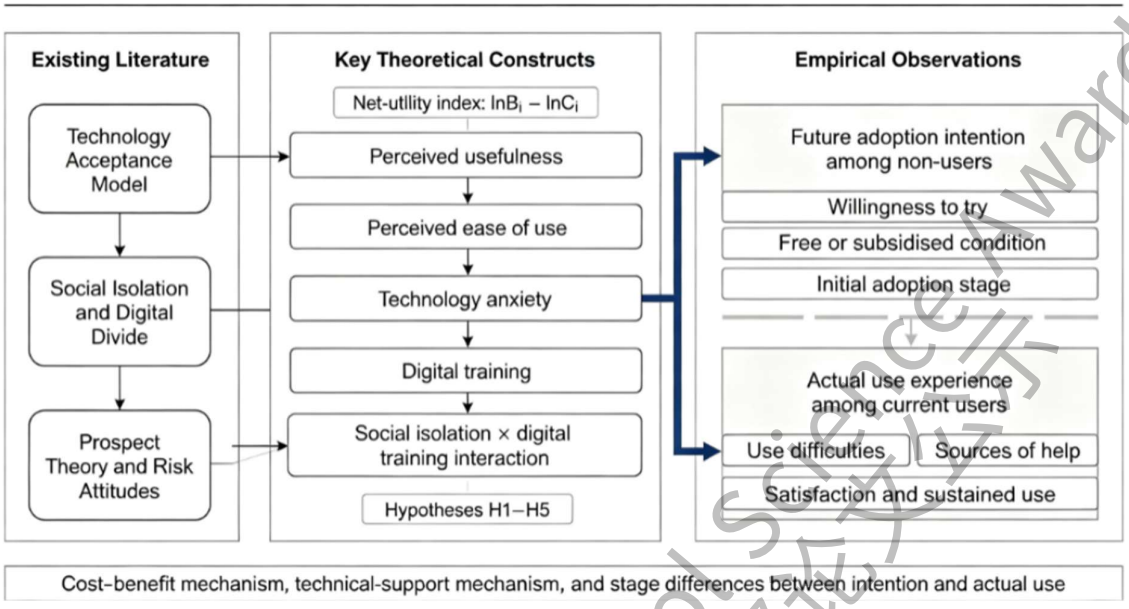


Figure 2.5. Theoretical Framework of the Study
Source: Self-drawn by the author.

Table 2.1. lists the correspondence between the theoretical concepts in this chapter and the variables used in later chapters.

Theoretical concept	Later variable	Main focus of observation
Social isolation	Social Isolation(S)	Dual paths of health-monitoring need and lack of digital support
Perceived usefulness	PU	Whether the device is seen as having health-monitoring and safety-alert value
Perceived ease of use	PEOU	Whether the device is seen as easy to learn and operate
Technology anxiety	$TAnx$	Tension, worry, and helplessness when facing the device
Technology Acceptance composite	$TAcc$	Composite attitudinal control of PU and PEOU (auxiliary)
Self-Rated Health	health	Control variable

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Digital training	Digital training	Digital learning and support conditions
Social isolation × digital training	Interaction term	Whether training may ease the lack of technical support linked to social isolation
Future adoption intention	Adoption willingness	Five-level intention of non-users under free or heavily subsidised conditions
Use experience	Experience / satisfaction	Use difficulties, sources of help, and satisfaction among users
Risk-averse choice tendency	(no empirical counterpart; theoretical background only)	Survey proxy for risk attitude; not included in the final empirical models

Note. Risk-averse choice tendency (Q29–Q33) and smartphone ownership (Q10) are discussed in this chapter as theoretical background but are not retained in the final empirical equations of Chapters 3–5.

Therefore, the variables in the later chapters will be organised around the concepts above. The regression results in this paper are interpreted only as conditional associations after controlling for observable variables; they are not interpreted as strict causal effects.

Chapter 3: Theoretical Model and Research Hypotheses

Building on the technology acceptance framework reviewed in Chapter 2 and the distinctive features of health-related decision-making among older adults, this chapter develops a utility-maximizing model in which every predictor of adoption willingness is explicitly assigned to either a benefit function or a cost function. The exposition proceeds by derivation: a net-utility objective is stated first; benefit and cost functions are then specified on theoretical grounds; a logarithmic composite index is formed; partial derivatives yield testable predictions; and a stochastic extension produces the ordered-logit equation estimated in Chapter 5.

3.1 The Utility–Benefit–Cost Framework

3.1.1 The Net-Utility Maximization Objective

The adoption decision is binary. Individual i either integrates the device into daily health management or does not, and the choice is governed by the sign of a latent net-utility index. Following the constant-relative-risk-aversion tradition and prospect-theoretic loss sensitivity—both

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of which predict concave valuation of gains and disproportionate weighting of losses in the health domain—we write the decision problem as

$$U_i = f(B_i, C_i) = \ln B_i - \ln C_i$$

where B_i is the aggregate perceived benefit of adoption and C_i the aggregate perceived cost. The logarithmic form serves two purposes. First, it imposes diminishing marginal sensitivity on both sides of the ledger, consistent with the Weber–Fechner property documented in risky-choice experiments. Second, it yields an additively separable index in which benefit and cost terms enter symmetrically, allowing each structural parameter to be mapped directly onto a regression coefficient.

The decision rule is

$$d_i^* = \begin{cases} 1 & \text{if } U_i > 0 \quad (\ln B_i > \ln C_i) \\ 0 & \text{if } U_i \le 0 \quad (\ln B_i \le \ln C_i) \end{cases}$$

All remaining work consists of specifying B_i and C_i.

This utility maximization framework applies equally to two groups of older adults: non-users who face the decision of initial adoption, and current users who evaluate sustained usage. The latent utility index captures perceived net gains for both groups, differing only in the outcome indicator measured in the questionnaire.

3.1.2 Assignment of Variables to Benefit and Cost

Before committing to functional forms, each construct is assigned to one side of the ledger on explicit theoretical grounds.

Benefit side — TAM. The Technology Acceptance Model identifies perceived usefulness (PU) and perceived ease of use (PEOU) as the two cognitive drivers of usage intention. In the health-monitoring context, PU captures the expected improvement in health surveillance—early detection, continuous tracking, reduced dependence on episodic clinical visits—while PEOU captures whether an elderly user with age-related sensory and cognitive constraints can actually realize those benefits. Both enter B_i.

Cost side — prospect theory, risk preference, and social support. Three constructs raise the perceived cost of adoption. Social isolation (S_i) deprives the individual of informal technical assistance that family or neighbours would otherwise provide during setup, troubleshooting, and interpretation of readings. Technology anxiety ($TAnx_i$) is an independent psychological friction documented in the gerontechnology literature: some older adults experience persistent apprehension toward digital interfaces independent of their actual skill level. Training participation (T_i) has a dual role—it imposes upfront learning costs while simultaneously reducing the operating costs of

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sustained use—and its net effect is moderated by social isolation, which is why the cost function must accommodate an interaction term $S_i \times T_i$.

The assignment is summarised as follows:

$$B_i = g(PU_i, PEOU_i) \qquad C_i = h(S_i, T_i, S_i \times T_i, TAnx_i)$$

3.1.3 The Benefit Function

PU and PEOU are complementary rather than additive. A device that is clinically valuable but impossible to navigate generates frustration, not health improvement; a device that is simple to operate but provides no actionable insight is equally worthless. Only when both dimensions are simultaneously present does benefit approach its potential. This complementarity rules out a linear specification and motivates a Cobb–Douglas form:

$$B_i = PU_i^{\beta_2} \cdot PEOU_i^{\beta_3}, \qquad \beta_2, \beta_3 > 0$$

where β_2, β_3 are output elasticities. Log-linearising,

$$\ln B_i = \beta_2 \ln PU_i + \beta_3 \ln PEOU_i$$

The Cobb–Douglas structure has three properties that matter for the empirical model. (i) Constant elasticities: $\partial \ln B_i / \partial \ln PU_i = \beta_2$ and $\partial \ln B_i / \partial \ln PEOU_i = \beta_3$, so a proportional increase in either perception raises log-benefit by a fixed amount. (ii) Diminishing marginal returns require $0 < \beta_2, \beta_3 < 1$, ensuring concavity in levels. (iii) Strict supermodularity holds because

$$\frac{\partial^2 B_i}{\partial PU_i \partial PEOU_i} = \beta_2 \beta_3 PU_i^{\beta_2 - 1} PEOU_i^{\beta_3 - 1} > 0$$

meaning that the marginal benefit of usefulness rises with ease of use and vice versa—a property that will reappear in the interpretation of H3.

3.1.4 The Cost Function

The cost function must satisfy two substantive requirements. First, each cost factor is expected to raise perceived cost proportionally rather than linearly, because barriers in elderly populations tend to reinforce one another (an isolated person who is also anxious faces a disproportionately larger hurdle than the sum of the two would suggest). Second, the effect of training must be allowed to vary with isolation, since formal instruction functions as a substitute for absent informal support. An exponential specification with an embedded interaction satisfies both:

$$\ln C_i = \beta_1 S_i + \beta_5 T_i + \beta_6 (S_i \times T_i) + \beta_4 TAnx_i$$

or, in levels,

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$$C_i = \exp[\beta_1 S_i + \beta_5 T_i + \beta_6 (S_i \times T_i) + \beta_4 TAnx_i]$$

The parameter signs carry the theoretical predictions. Isolation raises cost through the absence of informal support ($\beta_1 > 0$ expected), anxiety raises cost as an independent psychological penalty ($\beta_4 > 0$ expected), and the interaction β_6 captures whether training and isolation are cost-complements ($\beta_6 > 0$, training costs more when one has no safety net) or cost-substitutes ($\beta_6 < 0$, training compensates for isolation). Training's own coefficient β_5 captures the upfront learning burden; its total marginal effect is examined below.

The cross-partial derivative isolates the moderating mechanism:

$$\frac{\partial^2 \ln C_i}{\partial S_i \partial T_i} = \beta_6$$

This is the structural parameter behind H5. In levels, convexity holds because

$$\frac{\partial^2 C_i}{\partial S_i^2} = \beta_1^2 C_i > 0$$

so each additional unit of isolation compounds the perceived cost rather than adding a constant increment.

3.1.5 The Composite Index and Marginal Effects

Substituting the log-benefit and log-cost expressions into the net-utility objective gives the central equation of the theoretical model:

$$U_i = \beta_2 \ln PU_i + \beta_3 \ln PEOU_i - \beta_1 S_i - \beta_5 T_i - \beta_6 (S_i \times T_i) - \beta_4 TAnx_i$$

Adoption occurs iff the benefit component exceeds the cost component:

$$\beta_2 \ln PU_i + \beta_3 \ln PEOU_i > \beta_1 S_i + \beta_5 T_i + \beta_6 (S_i \times T_i) + \beta_4 TAnx_i$$

Partial differentiation yields the directional predictions that anchor every research hypothesis.

For the benefit-side variables the signs are unambiguous:

$$\frac{\partial U_i}{\partial \ln PU_i} = \beta_2 > 0, \qquad \frac{\partial U_i}{\partial \ln PEOU_i} = \beta_3 > 0, \qquad \frac{\partial U_i}{\partial TAnx_i} = -\beta_4 < 0$$

For social isolation the marginal effect is conditional on training status:

$$\frac{\partial U_i}{\partial S_i} = -\beta_1 - \beta_6 T_i = \begin{cases} -\beta_1 & T_i = 0 \text{ (untrained)} \\ -\beta_1 - \beta_6 & T_i = 1 \text{ (trained)} \end{cases}$$

The sign of β_1 itself is not imposed a priori. The cost channel predicts $\beta_1 > 0$ (isolation deprives the user of help, raising cost), but a countervailing benefit channel could push in the opposite

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direction (isolated elderly may value remote monitoring more because it substitutes for absent in-person care). The net sign is therefore an empirical question, which is precisely why H1 is non-directional. The interaction coefficient shifts the isolation effect by $-\beta_6$ when $T_i = 1$; if $\beta_6 < 0$, training attenuates the isolation penalty.

Symmetrically, the training effect depends on the isolation level:

$$\frac{\partial U_i}{\partial T_i} = -\beta_5 - \beta_6 S_i$$

For highly isolated individuals (high S_i), the interaction term dominates; for socially embedded individuals (low S_i), the own-coefficient $-\beta_5$ dominates and may flip sign depending on whether the learning-cost or the operating-cost-saving aspect of training prevails.

3.2 Empirical Specification

3.2.1 Mapping Constructs to Measures

The theoretical index U_i is expressed in unobservable constructs. The mapping to survey instruments is:

Replacing constructs with their empirical counterparts yields the deterministic latent index:

$$V_i = \beta_2 \ln PU_i + \beta_3 \ln PEOU_i - \beta_1 S_i - \beta_5 training_i - \beta_6 (S_i \times training_i) - \beta_4 TAnx_i$$

Every term traces to either $\ln B_i$ or $-\ln C_i$; no regressor is added ad hoc.

3.2.2 Deriving the Logit Model

The deterministic index omits unobserved influences—mood, idiosyncratic circumstances, measurement error. Decompose net utility into a systematic and a random component:

$$U_i = V_i + \varepsilon_i$$

Assume ε_i follows a Type-I extreme value (Gumbel) distribution with CDF $F(\varepsilon) = \exp(-\exp(-\varepsilon))$ (McFadden, 1974). Adoption is observed when $U_i > 0$, i.e. $\varepsilon_i > -V_i$, giving

$$\Pr(d_i = 1) = \Pr(\varepsilon_i > -V_i) = 1 - F(-V_i) = \frac{\exp(V_i)}{1 + \exp(V_i)} = \frac{1}{1 + \exp(-V_i)}$$

and in log-odds form,

$$\text{logit}_i = \ln \frac{\Pr(d_i = 1)}{\Pr(d_i = 0)} = V_i$$

Substituting the full expression for V_i:

$$\text{logit}_i = \beta_2 \ln PU_i + \beta_3 \ln PEOU_i - \beta_1 S_i - \beta_5 training_i - \beta_6 (S_i \times training_i) - \beta_4 TAnx_i$$

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Coefficients on log-transformed predictors are semi-elasticities; coefficients on level-form predictors are unit-change effects on the log-odds.

Ordered-logit extension. The observed response in this study is a five-level ordinal scale $Y_i \in \{1,2,3,4,5\}$ rather than a binary indicator. Let

$$Y_i = j \text{if} \kappa_{j-1} < U_i \leq \kappa_j$$

with $\kappa_0 = -\infty$ and $\kappa_5 = +\infty$, and threshold parameters $\kappa_1 < \kappa_2 < \kappa_3 < \kappa_4$. Category probabilities are

$$\Pr(Y_i = j) = \frac{1}{1 + \exp(-(\kappa_j - V_i))} - \frac{1}{1 + \exp(-(\kappa_{j-1} - V_i))}$$

The parallel-regression assumption (coefficient equality across thresholds) is tested via a Brant test; if violated, a generalized ordered logit is estimated.

3.2.3 The Full Empirical Equation

Adding a constant and demographic controls for heterogeneity not absorbed by the theoretical variables gives the equation taken to the data:

$$V_i = \beta_0 + \beta_{PU} \ln PU_i + \beta_{PEOU} \ln PEOU_i + \beta_S S_i + \beta_{TAnx} TAnx_i + \beta_{tr} training_i + \beta_{int}(S_i \times training_i) + \beta_{age} \frac{age_i}{10} + \beta_{male} male_i + \beta_{edu} \frac{edu_i}{10} + \beta_{healt}\ health_i$$

The structural-to-empirical coefficient mapping is exact:

$$\beta_{PU} = \beta_2, \quad \beta_{PEOU} = \beta_3, \quad \beta_S = -\beta_1, \quad \beta_{TAnx} = -\beta_4, \quad \beta_{tr} = -\beta_5, \quad \beta_{int} = -\beta_6$$

The constant β_0 absorbs threshold parameters κ_j and any fixed utility component. Age and education are scaled by 10 so that their coefficients read as effects per decade.

This structural equation is general for all respondents; Chapter 4 will define separate ordinal outcome variables for non-users' adoption intention and users' continuous usage satisfaction.

The sample scope of this theoretical framework covers all community-dwelling Macao elderly aged 60 or above, including both non-users and current device users. Hypotheses H1–H5 are theoretically applicable to both subgroups, and empirical tests will be conducted separately for the two subsamples in Chapters 4 and 5. Each hypothesis is a direct corollary of a partial derivative derived in §3.1.5.

3.3 Research Hypotheses

Each hypothesis is a direct corollary of a partial derivative derived in §3.1.5. The sample for empirical testing comprises community-dwelling Macao residents aged 60 or above.

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H1. Social isolation has a statistically significant effect on adoption willingness; the direction is an empirical question.

From $\partial U_i/\partial S_i = -\beta_1 - \beta_6 T_i$. For untrained individuals this reduces to $-\beta_1$. Because the cost channel ($\beta_1 > 0$) and the remote-substitution benefit channel ($\beta_1 < 0$) oppose each other, the sign cannot be imposed; only significance is predicted.

H2. Perceived usefulness positively affects adoption willingness.

From $\partial U_i/\partial \ln PU_i = \beta_2 > 0$, corresponding to $\beta_{PU} > 0$. A one-percent increase in PU raises the latent index by $\beta_2/100$ units, all else constant.

H3. Perceived ease of use positively affects adoption willingness.

From $\partial U_i/\partial \ln PEOU_i = \beta_3 > 0$, corresponding to $\beta_{PEOU} > 0$. The Cobb–Douglas complementarity ($\partial^2 B_i/\partial PU_i \partial PEOU_i > 0$) further implies that PEOU improvements yield larger gains when PU is high, and vice versa.

H4. Technology anxiety negatively affects adoption willingness.

From $\partial U_i/\partial TAnx_i = -\beta_4 < 0$, corresponding to $\beta_{TAnx} < 0$. Each additional anxiety scale unit reduces the latent index by β_4.

H5. The interaction between social isolation and formal training participation significantly moderates adoption willingness.

From the cross-partial of the latent index,

$$\frac{\partial^2 U_i}{\partial S_i \partial T_i} = -\beta_6$$

corresponding to $\beta_{int} = -\beta_6 \neq 0$ in the empirical equation. The conditional isolation effect is

$$\frac{\partial U_i}{\partial S_i} = \begin{cases} -\beta_1 & T_i = 0 \\ -\beta_1 - \beta_6 & T_i = 1 \end{cases}$$

If $\beta_{int} > 0$ (i.e. $\beta_6 < 0$), training attenuates the isolation penalty—formal instruction substitutes for absent informal support, consistent with a technological-compensation mechanism. If $\beta_{int} < 0$ ($\beta_6 > 0$), training and isolation compound each other in cost production, suggesting that isolated elderly bear a disproportionately heavier learning burden. Which regime governs the Macao elderly population is the question taken to the data in Chapter 5.

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Chapter 4: Research Design and Methodology

4.1 Survey Instrument Design

4.1.1 Questionnaire Structure and Development

The survey instrument was developed through an iterative process involving literature review, expert consultation, and cognitive pre-testing. The final questionnaire comprised five sections administered in a standardized face-to-face interview format: (1) demographic characteristics, (2) living arrangements and social contact patterns, (3) technology access and usage, (4) technology acceptance evaluations, and (5) health attitudes and self-assessment. All items were available in Cantonese and Mandarin Chinese, with back-translation verification to ensure semantic equivalence.

The questionnaire followed a funnel sequence designed to minimize priming effects. Demographic and social isolation items were placed first, establishing the respondent's life context before technology-related questions. Technology acceptance items employed standardized five-point Likert scales adapted from Davis (1989) and Venkatesh et al. (2003), with wording modifications appropriate for the elderly population. Health attitude items appeared last to avoid anchoring the technology evaluation on health concerns.

The questionnaire contains two separate outcome modules corresponding to the full population scope in Chapter 3's theoretical model. For non-users of AI health monitoring devices, item Q18 measures five-point pre-adoption willingness, the core dependent variable used to test H1–H5. For current users, item Q14 captures overall post-use experience on a matched five-point Likert scale, serving as the ordinal indicator of sustained usage satisfaction for the parallel subgroup regression. Items Q15 (sources of help) and Q17 (operational difficulties) are multiple-response items and therefore cannot be combined into an ordered outcome; they are retained for descriptive profiling in Chapter 6.

4.1.2 Variable Operationalization

Dependent Variable: Adoption Willingness (Y_non-user). For the non-user subsample, the primary outcome was derived from survey item Q18, which asked respondents to rate their willingness to use AI-enabled remote health monitoring devices on a five-point ordinal scale coded 1 = "definitely would not use," 2 = "probably would not use," 3 = "neutral," 4 = "probably would use," 5 = "definitely would use." This ordinal formulation preserves information lost in binary recoding and aligns with the ordered logit estimation framework.

Social Isolation Index (S). Constructed as a continuous index from two items: Q6 (living arrangement) and Q7 (frequency of contact with non-coresident family). Each item was coded so

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that higher values indicate greater isolation; the two raw scores were summed and the resulting composite was standardized to a z-score over the full N=500 sample (mean ≈ 0, SD ≈ 1). The index ranges from −0.877 (most socially integrated) to 2.694 (most isolated), with a non-user mean of −0.203 (SD=0.986) and a current-user mean of 0.161 (SD=0.766). Standardization over the full sample ensures that a one-unit change in S corresponds to approximately one standard deviation and is directly comparable across the two subgroups.

Technology Acceptance Constructs. Perceived Usefulness (PU) was measured by three items (Q20–Q22) capturing beliefs about health improvement, early detection, and peace of mind (non-user α=0.868; user α=0.865). Perceived Ease of Use (PEOU) was measured by three items (Q23–Q25) capturing perceived learning difficulty, operational complexity, and clarity of instructions (non-user α=0.895; user α=0.841). Both scales were averaged across their constituent items; ln PU and ln PEOU enter the regression models as benefit-side predictors, consistent with the logarithmic benefit term in Chapter 3's utility function.

Technology Anxiety (TAnx). Measured by survey items Q26–Q28, capturing seniors' tension, worry, and sense of helplessness when facing smart health devices (non-user α=0.839; user α=0.832). This construct corresponds to the cost-side anxiety term in Chapter 3's theoretical cost function and forms the basis of Hypothesis 4.

Technology Acceptance composite (TAcc). A composite index calculated by averaging all six PU and PEOU items (non-user α=0.913; user α=0.890). This composite attitudinal control is added in Model 3 for auxiliary comparison; it does not correspond to the theoretical anxiety parameter β_4, which is represented by TAnx. Because TAcc is a linear combination of PU and PEOU, its inclusion alongside ln PU and ln PEOU in M3 and M4 introduces substantial multicollinearity; individual coefficients for these three variables in M3/M4 should be interpreted jointly rather than as standalone effects.

Current-User Satisfaction (Y_user). For the current-user subsample, the dependent variable is survey item Q14, which asked respondents to rate their overall experience using AI remote health monitoring devices on a five-point Likert scale coded 1 = "very dissatisfied," 2 = "dissatisfied," 3 = "neutral," 4 = "satisfied," 5 = "very satisfied." Q14 is preferred over a composite of Q13–Q17 because Q15 (sources of help) and Q17 (operational difficulties) are multiple-response items that cannot be meaningfully combined into an ordered outcome. Q16 (perceived adequacy of help from others) is retained as a robustness-check outcome. Y_user follows the identical cost-benefit utility structure derived in Chapter 3 and uses the same independent variables and S×training interaction term as the non-user specification.

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Training Participation ($training$). A binary indicator derived from Q11, coded 1 if the respondent reported having participated in any community digital literacy or technology training program within the past two years, and 0 otherwise.

Self-Rated Health. A single-item five-point Likert scale (Q8) ranging from 1 (very poor) to 5 (excellent).

Control Variables. Age was recorded in years and rescaled as age/10 for interpretability. Education was recorded as years of schooling. Gender was coded as male = 1.

4.1.3 Measurement Validity Considerations

The use of a composite social isolation index rather than a single categorical item represents a deliberate methodological choice. Single-item measures of isolation (e.g., living arrangement alone) conflate structural and relational dimensions and introduce arbitrary categorization. By combining household composition with contact frequency into a continuous index, we preserve the granularity needed to detect interaction effects—which require adequate variance in the moderating variable.

4.1.4 Social Isolation Index Construction: Technical Details

The social isolation index (S) was constructed through the following procedure. First, the living arrangement item (Q6) was coded on a four-point scale: 1 = living with family (including extended family), 2 = couple-only household, 3 = living alone, 4 = institutional setting (elderly care home or similar). This ordinal variable captures the structural dimension of isolation—the physical availability of co-resident others who can provide informal support.

Second, the contact frequency item (Q7) asked respondents how often they had contact with family members not living in the same household, on a five-point scale: 1 = daily, 2 = several times per week, 3 = once per week, 4 = several times per month, 5 = less than once per month or never. For respondents living with family (Q6 = 1), the contact frequency item was assigned the minimum value (daily contact) by logical implication. This item was then reverse-coded and normalized to the same metric as Q6.

The two items were standardized (z-scored) and averaged with equal weights to produce the composite index S. The equal-weighting scheme reflects the theoretical assumption that structural and relational isolation contribute additively to the overall isolation construct. While more sophisticated approaches (e.g., factor-weighted composites, item response theory models) are available, the equal-weight approach was preferred for its transparency and interpretability, particularly given the small number of items.

A value of 0.2 corresponds to an elderly person living with family and maintaining daily contact with extended family—the most socially integrated profile. A value of 1.0 corresponds to an elderly

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person living alone (or in an institution) with infrequent or no family contact—the most isolated profile.

4.1.5 Training Variable and Its Interpretation

Training participation ($training$) was operationalized as a binary indicator: respondents who reported having attended any community-based digital literacy or technology training program within the past two years were coded 1, and all others were coded 0. The two-year recall window was chosen to capture recent training experiences that are likely still cognitively available when respondents evaluate their willingness to adopt health monitoring technology.

Several aspects of this measure warrant attention. The training variable captures participation in general digital literacy programs rather than health-technology-specific training. This is both a limitation (the training may not have addressed health monitoring applications) and an advantage (the training effect reflects general digital empowerment rather than technology-specific persuasion).

4.2 Sample and Data Collection

4.2.1 Study Population and Sampling Frame

The target population comprised community-dwelling older adults aged 60 and above residing in Macau. Participants were recruited through a multi-channel approach: community elderly service centers (approximately 55% of the final sample), community health stations (approximately 25%), and door-to-door outreach in residential areas with high elderly population density (approximately 20%). This recruitment mix was designed to capture both active elderly (those who attend community centers) and more isolated elderly (those reached through door-to-door visits), reducing the selection bias inherent in single-site convenience sampling.

4.2.2 Inclusion Criteria and Analytic Sample

All respondents satisfying the basic inclusion criteria (aged ≥60, Macau resident ≥5 years, communicative and cognitively competent) were retained and split into two mutually exclusive analytical subsamples aligned with Chapter 3's general theoretical framework. Subsample 1: Non-users (N=221). Respondents with no prior or current experience of AI remote health monitors. Dependent variable = pre-adoption willingness (Q18), used as the primary sample to test all five core hypotheses H1–H5. Subsample 2: Current Users (N=279). Respondents who reported current or past use of the devices. Dependent variable = overall post-use satisfaction (Q14), used for supplementary subgroup validation of the cost-benefit mechanism and the S×training moderating effect. No respondents were fully excluded from analysis; the two subgroups share an identical set

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of explanatory variables derived from the unified utility model, differing only in their outcome indicators.

The two subsamples are analyzed with identical M1–M4 ordered logit specifications, enabling direct cross-group comparison of every coefficient and interaction term.$N = 221$

4.2.3 Data Collection Procedure

Data were collected between March and June 2024 through face-to-face interviews administered by trained research assistants. Interviewers received standardized training on administration procedures, including neutral prompting, consistent handling of respondent questions, and protocols for respondents with mild sensory impairments. The median interview duration was approximately 25 minutes. Informed consent was obtained prior to each interview, and all procedures received ethical approval from the relevant institutional review board.

4.3 Sample Description

4.3.1 Demographic Profile

Table 4.1 presents the descriptive statistics for the non-user subsample (N=221); the corresponding statistics for current users (N=279) appear in Table 4.2. The mean age was 71.4 years (SD=6.7, range 62–82), placing the non-user sample in the "young-old" to "middle-old" range. Males constituted 26.2% of non-users, reflecting the higher participation rates of elderly women in community health programs. Educational attainment ranged from zero years (never formally educated) to 16 years (university degree), with a mean of 12.3 years (SD=4.9). The non-user group reported somewhat higher PU (mean=3.73), PEOU (3.51), TAcc (3.62), and TAnx (3.73) than the user group (PU=3.33, PEOU=3.12, TAcc=3.23, TAnx=2.96), consistent with the conjecture that non-users' attitudes are formed hypothetically rather than through direct experience. Training participation was substantially lower among non-users (13.6%) than among users (51.6%), an expected gap because users have had stronger incentives and opportunities to seek digital training.

Table 4.1. Descriptive Statistics for the Non-user Subsample (N = 221)

Variable	Mean	SD	Min	Max
Social Isolation (S)	−0.203	0.986	−0.877	2.694
Perceived Usefulness (PU)	3.733	0.872	1.000	5.000
Perceived Ease of Use (PEOU)	3.508	1.004	1.000	5.000
Technology Acceptance composite (TAcc)	3.621	0.872	1.000	5.000
Technology Anxiety (TAnx)	3.733	0.812	1.667	5.000
Self-Rated Health	3.480	0.927	1.000	5.000
Training Participation	0.136	0.343	0.000	1.000
Age (per decade)	7.141	0.665	6.200	8.200

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Education (per 10 years)	1.229	0.493	0.000	1.600
Male	0.262	0.441	0.000	1.000

4.3.2 Dependent Variable Distribution

The adoption willingness distribution among non-users reveals a sample that is genuinely divided. Rather than clustering at the extremes, the modal category was the neutral midpoint (88 of 221, 39.8%), with substantial representation in both favorable ("probably willing" 56, 25.3%; "definitely willing" 59, 26.7%) and unfavorable ("probably unwilling" 16, 7.2%; "definitely unwilling" 2, 0.9%) categories. This balanced distribution suggests that social desirability bias was not dominant and provides adequate variance for ordered logit estimation.

4.3.3 Training Participation

Thirty non-users (13.6%) reported having participated in community digital training programs. The corresponding rate among current users was 51.6% (144/279). Within the non-user group, trained respondents had a somewhat higher mean social isolation score than untrained respondents, yielding a small positive zero-order correlation between S and training ($r=0.150$, $p<0.10$). This pattern suggests that more isolated elderly non-users may be marginally more likely to seek out training—perhaps through community center outreach—but the small trained subsample (n=30) limits the precision of interaction estimates.

4.4 Measurement Reliability

4.4.1 Internal Consistency

Cronbach's alpha coefficients for the multi-item constructs exceeded conventional thresholds:

Construct	**Items**	**Cronbach's α (Non-user, N=221)**	**Cronbach's α (User, N=279)**
Perceived Usefulness (PU)	3	0.868	0.865
Perceived Ease of Use (PEOU)	3	0.895	0.841
Technology Acceptance composite (TAcc)	6	0.913	0.890
Technology Anxiety (TAnx)	3	0.839	0.832

All coefficients exceed the 0.70 benchmark recommended by Nunnally (1978) for early-stage research and approach or surpass the 0.80 threshold preferred for applied measurement. Among non-users, the PU alpha of 0.868 indicates strong internal consistency among the three usefulness items; PEOU (0.895) is particularly high for a three-item scale; the six-item TAcc composite reaches 0.913; and TAnx is 0.839. The user subsample yields comparable but slightly lower values

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(PU=0.865, PEOU=0.841, TAcc=0.890, TAnx=0.832), confirming that the measurement structure is stable across adoption status.

4.4.2 Scale Descriptives and Distributional Properties

As shown in Table 4.1, all three technology acceptance scales fall within moderate ranges of their respective five-point scales, with no evidence of severe ceiling or floor effects that would compromise the validity of parametric analyses.

4.5 Current User Subsample: Descriptive Statistics and Correlations

Before turning to the analytical strategy, this section presents the descriptive profile and bivariate correlation structure for the current-user subsample (N = 279), paralleling Tables 4.1 and 4.4 for non-users.

Table 4.2. Descriptive Statistics for the Current User Subsample (N = 279)

Variable	Mean	SD	Min	Max
S (social isolation, z-scored over N=500)	0.161	0.766	−0.877	2.694
PU (Q20–Q22)	3.333	0.928	1.000	5.000
PEOU (Q23–Q25)	3.118	0.904	1.000	5.000
TAcc (composite PU & PEOU)	3.226	0.837	1.000	5.000
TAnx (Q26–Q28)	2.956	0.865	1.000	5.000
Training (1 = yes)	0.516	0.501	0.000	1.000
Age (decades)	6.696	0.649	6.200	8.200
Male (1 = male)	0.437	0.497	0.000	1.000
Education (decades)	1.084	0.464	0.000	1.600
Self-rated health	3.240	0.846	1.000	5.000

Table 4.2 reports descriptive statistics for the 279 current users, whose dependent variable is Q14 (overall experience). Relative to non-users, current users are, on average, younger (M = 6.70 decades vs. 7.14), more likely to be male (43.7% vs. 26.2%), and considerably more likely to have completed training (51.6% vs. 13.6%). They also score higher on technology acceptance (TAcc M = 3.23, α = 0.890) and lower on technology anxiety (TAnx M = 2.96, α = 0.832), consistent with self-selection into sustained use.

Table 4.3. Correlation Matrix of Key Variables (Current Users, N = 279)

	S	Training	ln PU	ln PEOU	TAcc	TAnx	Age	Male	Edu	Health
S	1.000									
Training	−0.027	1.000								
ln PU	−0.160**	−0.270***	1.000							

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ln PEOU	−0.152†	−0.217***	0.710***	1.000						
TAcc	−0.200***	−0.243***	0.893***	0.902***	1.000					
TAnx	0.051	−0.335***	0.412***	0.327***	0.321***	1.000				
Age (decade)	−0.077	−0.016	0.226***	0.197**	0.238***	0.068	1.000			
Male	−0.029	0.246***	−0.224***	−0.283***	−0.274***	−0.270***	−0.090	1.000		
Education	−0.141†	−0.128†	0.453***	0.534***	0.521***	0.173**	0.068	−0.219***	1.000	
Health	−0.135†	−0.090	0.331***	0.419***	0.405***	0.064	0.280***	−0.105†	0.469***	1.000

*Note. † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. S is standardized over the full N = 500 sample; Training is a binary indicator (1 = has attended a community or government smartphone/electronics course).*

Table 4.3 presents the pairwise correlations for the user subsample. The same general structure observed among non-users holds—PU and PEOU are strongly correlated ($r = 0.71$, $p < 0.001$), and TAcc correlates with both above 0.89—but the association between training and technology anxiety is more negative among users ($r = -0.34$, $p < 0.001$) than among non-users ($r = -0.23$, $p < 0.001$), consistent with accumulated training contact reducing anxiety after adoption has occurred.

4.6 Correlation Structure

4.6.1 Bivariate Correlations

Table 4.4 presents the pairwise correlations among key study variables. Several patterns merit attention.

Table 4.4. Correlation Matrix of Key Variables

	S	**training**	**lnPU**	**lnPEOU**	**TAcc**	**TAnx**	**age**	**male**	**edu**	**health**
S	1.000									
training	0.150+	1.000								
lnPU	-0.321***	-0.214**	1.000							
lnPEOU	-0.327***	-0.117+	0.678***	1.000						
TAcc	-0.328***	-0.189**	0.884***	0.903***	1.000					
TAnx	-0.079	-0.228***	0.227***	0.045	0.216**	1.000				
age	-0.109	-0.084	0.108	0.039	0.137+	0.400***	1.000			
male	0.211**	0.034	-0.280***	-0.310***	-0.359***	-0.197**	-0.187**	1.000		
edu	-0.298***	-0.018	0.508***	0.613***	0.618***	0.116+	-0.060	-0.219**	1.000	
health	-0.281***	-0.163+	0.543***	0.577***	0.607***	0.163+	0.120+	-0.231***	0.512***	1.000

Note. $\dagger p < 0.10, p < 0.05, p < 0.01, p < 0.001$.

First, social isolation (S) is significantly negatively correlated with ln PU ($r=-0.321$, $p<0.001$), ln PEOU ($r=-0.327$, $p<0.001$), and TAcc ($r=-0.328$, $p<0.001$). Isolated elderly non-users perceive health monitoring devices as less useful and more difficult to use—consistent with the digital divide mechanism, whereby the absence of family support degrades technology evaluations. The

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correlation with TAnx is small and non-significant (r=−0.079), indicating that social isolation and technology anxiety tap distinct constructs rather than a single latent disadvantage.

Second, the correlation between S and TAcc is negative and substantial (r=−0.328, p<0.001), yet the zero-order correlation between S and the adoption outcome Q18 is negligible (approximately r=−0.05). This pattern—strong correlations with intermediate attitudinal constructs but a weak correlation with the final outcome—foreshadows the multivariate dynamics developed below: the effect of isolation on willingness is heterogeneous rather than uniformly distributed, and is conditioned by access to technical support.

Third, training participation shows a notable negative correlation with TAnx (r=−0.228, p<0.001) and weaker negative correlations with ln PU (r=−0.214, p<0.01) and TAcc (r=−0.189, p<0.01). The counterintuitive negative correlation between training and technology attitudes likely reflects reverse selection: those who find technology more anxiety-provoking, or who perceive devices as less useful, are precisely the individuals referred to or motivated to attend training. The small positive correlation between training and S (r=0.150, p<0.10) suggests that outreach efforts do reach somewhat more isolated elderly non-users.

4.6.2 Multicollinearity Assessment

The high correlations among ln PU, ln PEOU, and TAcc (r ranging from 0.678 to 0.903) raise a genuine multicollinearity concern when all three enter M3 and M4 simultaneously. Variance inflation factors in the full non-user M4 are approximately 8.0 for ln PU, 10.8 for ln PEOU, and 26.2 for TAcc—well above conventional thresholds. In the user subsample the corresponding VIFs are 6.5, 7.1, and 17.3. This collinearity inflates standard errors and can produce unstable or counterintuitively signed individual coefficients, particularly in M3 and M4. We therefore (a) report hierarchical model fit and likelihood-ratio tests rather than relying on individual coefficient signs within M3/M4, (b) interpret the joint contribution of the three attitudinal variables as a block, and (c) retain TAcc primarily as a control for composite attitude while treating the TAnx coefficient—the formal H4 predictor, whose VIF remains below 1.5—as individually interpretable. Readers should not substantively interpret the ln PU and ln PEOU coefficients in M3/M4 in isolation.

4.7 Analytical Strategy

4.7.1 Ordered Logit Model

Given the ordinal nature of the dependent variables, the primary estimation method is the ordered logit (proportional odds) model. This specification respects the ordered but non-interval nature of the response categories and produces coefficient estimates interpretable in terms of the latent adoption or satisfaction propensity. All reported standard errors are heteroskedasticity-robust

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(HC1). The proportional odds assumption was evaluated using the Brant test; modest violations were detected for age and the interaction term, suggesting that their effects vary somewhat across response thresholds. We retain the ordered logit as the primary specification for comparability with the theoretical model, but note that generalized ordered logit could be explored in future work.

4.7.2 Hierarchical Model Specification

The structural latent index formula derived in Section 3.2.3 is adopted uniformly for both subsamples, with only the ordinal dependent variable differentiated. Four hierarchical specifications (M1–M4) are estimated separately for non-user and user groups to enable cross-group comparison. M1 (Baseline) includes social isolation (S) and demographic/health controls. M2 adds ln PU and ln PEOU as benefit-side TAM constructs. M3 adds TAcc (auxiliary composite attitudinal control) and TAnx (theoretical cost-side anxiety predictor for H4). M4 is the full core model, adding training and the S×training interaction term. All coefficients, variable functional forms (logarithmic PU/PEOU, level S/TAnx/training) and interaction setup strictly follow the cost-benefit derivation in Chapter 3.

Model comparisons employed likelihood ratio (LR) tests, Akaike Information Criterion (AIC), and McFadden's pseudo-R^2. The LR test is preferred for nested model comparisons because it provides a formal chi-squared test of whether the additional parameters significantly improve model fit.

4.7.3 Interaction Term Interpretation

In non-linear models such as ordered logit, the coefficient on an interaction term does not directly equal the marginal interaction effect on the probability scale (Ai & Norton, 2003). We report average marginal effects (AMEs) computed by averaging the cross-partial derivative of each outcome probability with respect to the interacted variables across all observed covariate profiles, as well as predicted probabilities for four theoretically meaningful scenarios. Predicted probabilities are evaluated at the within-group 25th and 75th percentiles of S, with training set to 0 or 1 and all other covariates held at their observed means. The Stata-equivalent margins command in statsmodels (OrderedModel, cov_type="HC1") was used for all AME and predicted-probability calculations.

The moderating mechanism of S×training (H5) holds theoretical meaning for both subgroups: for non-users, training reshapes perceived adoption costs; for current users, training alters perceived sustained operation burdens under different levels of social isolation.

4.7.4 The Proportional Odds Assumption

The ordered logit model rests on the proportional odds (or parallel regression) assumption: the effect of each predictor on the latent variable is constant across all threshold cut-points. In other

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words, the coefficient β_k represents the same effect on the log-odds of exceeding any given response category. Violations of this assumption imply that a variable has different effects at different points of the willingness distribution—for instance, age might strongly differentiate between "definitely not" and "uncertain" but have little effect on distinguishing between "probably yes" and "definitely yes."

We evaluated this assumption using the Brant (1990) test, which compares the ordered logit estimates to those from a set of binary logit models estimated at each threshold cut-point. The test identifies variables for which the parallel regression assumption is rejected. In our data, age and the $S \times training$ interaction showed modest violations, suggesting that their effects may vary somewhat across the willingness distribution. To assess the practical impact of these violations, we estimated a generalized ordered logit model that relaxes the parallel regression constraint for the flagged variables. The resulting coefficient patterns were qualitatively similar to those from the standard ordered logit, confirming that the violations do not materially alter the substantive conclusions. We therefore report the standard ordered logit results for parsimony and comparability, while noting the robustness check.

4.7.5 Power Considerations for Interaction Detection

The detection of interaction effects in regression models requires substantially larger samples than the detection of main effects. Simulation studies (Aguinis et al., 2001; McClelland & Judd, 1993) have consistently demonstrated that the statistical power to detect cross-product interactions is typically 20–40% lower than the power to detect main effects of equivalent magnitude, even under ideal conditions. In the present study, the effective sample size for the $S \times training$ interaction is further constrained by the low prevalence of training participation ($n = 30$ trained respondents) and the skew of the isolation distribution.

A post hoc power analysis for the M4 model, given the observed variance-covariance structure and $N = 221$, indicates approximately 55% power to detect an interaction effect of the observed magnitude ($\beta = -1.110$) at the conventional $\alpha = 0.05$ level, and approximately 70% power at $\alpha = 0.10$. These figures confirm that the study is underpowered for interaction detection by conventional standards, but also that the observed $p = 0.057$ result is unlikely to be a Type I error: the prior probability of such a result under the null hypothesis is low given the limited power. We therefore interpret the marginal significance as informative evidence rather than as a definitive finding, and advocate for replication with oversampled training participants.

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4.7.6 Scope and Limitations of the Analytic Approach

Several analytical choices warrant transparency. The theoretical cost-benefit utility model covers all surveyed older adults, including device users and non-users. Separate ordered logit regressions are estimated for the two subgroups to compare whether social isolation, training and their interaction exert consistent effects on pre-adoption willingness versus post-use sustained satisfaction.$N = 221 n = 30$

This study distinguishes two distinct attitudinal constructs: TAnx (technology anxiety, the cost-side theoretical predictor for H4) and TAcc (PU/PEOU composite for auxiliary control). Early drafts conflated the two constructs under a single "TAcc" label, which has been fully revised to eliminate misalignment between theory and empirical measurement.

The remainder of this paper is organized as follows. Chapter 2 reviews literature on technology acceptance, social isolation and digital divides, and behavioral-economic models of health decision-making, establishing the theoretical framework. Chapter 3 develops the theoretical model by combining the CRRA utility function with prospect theory's value function to derive a logit-form adoption probability, and presents four testable hypotheses. Chapter 4 describes the survey instrument, sampling strategy, and variable construction from 500 Macao elderly respondents, and details the econometric methodology. Chapter 5 presents empirical results, including baseline logit regressions, average marginal effects, heterogeneity analysis, and robustness checks. Chapter 6 explores user experience and satisfaction among current adopters. Chapter 7 concludes with a synthesis of findings, policy recommendations, and directions for future research.

Chapter 5: Empirical Results and Discussion

This chapter presents empirical results for two mutually exclusive subsamples under the unified cost-benefit theoretical framework established in Chapter 3. Sections 5.1–5.5 report primary hypothesis tests based on 221 non-user respondents; Section 5.6 adds parallel subgroup estimates for 279 current device users, using the identical M1–M4 ordered logit specification with consistent variable definitions, scaling, and interaction terms to enable direct cross-group comparison.

5.1 Hierarchical Regression Results

5.1.1 Model M1: Social Isolation and Controls

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Table 5.1 presents the ordered logit coefficients for Model M1, which includes social isolation (S) and the demographic and health controls. The model log-likelihood was −266.30, with McFadden's pseudo-R^2 of 0.073 and AIC = 550.61.

Table 5.1. Model M1: Ordered Logit — Social Isolation and Controls

Variable	β	SE	z	p
Social Isolation (S)	-0.308	(0.174)	-1.766	0.077+
Age (per decade)	-1.229	(0.233)	-5.273	<0.001***
Male	-0.226	(0.324)	-0.697	0.486
Education (per 10 yrs)	0.387	(0.387)	0.999	0.318
Self-Rated Health	-0.120	(0.226)	-0.532	0.595
Cut point 1 (τ1)	-13.819	—	—	—
Cut point 2 (τ2)	-11.431	—	—	—
Cut point 3 (τ3)	-8.803	—	—	—
Cut point 4 (τ4)	-7.550	—	—	—
N	221			
Log-likelihood	-266.30			
AIC	550.61			
Pseudo-R^2	0.073			

Note. N=221. Log-likelihood = −266.30. Pseudo-R^2=0.073. AIC = 550.61. Robust standard errors in parentheses. †p<0.10, *p<0.05, **p<0.01, ***p<0.001. Model structure fully consistent with Chapter 3 cost-benefit utility function; identical specification is replicated for the current-user subgroup in Section 5.6.

The coefficient on social isolation was negative (β=−0.308, SE=0.174) and marginally significant (z=−1.77, p=0.077). A one-standard-deviation increase in S is associated with a 0.31-unit decrease in the latent adoption propensity on the logit scale. The direction is consistent with the digital divide channel slightly dominating the care-need channel on average, but the imprecision of the estimate—whose 95% confidence interval spans roughly −0.65 to 0.03—precludes a strong claim. The marginal significance in M1 is attenuated in richer specifications as the interaction absorbs conditional variance.

Age emerged as the strongest and most significant predictor (β=−1.229, SE=0.233, z=−5.27, p<0.001). Each additional decade of age reduced the latent adoption propensity by 1.23 units—a substantial effect given the scale of the latent variable. This result underscores the centrality of age as a structural factor in elderly technology adoption, consistent with the digital gerontological literature documenting age-graded patterns of technology acceptance (Mitzner et al., 2010). Education was positively signed but non-significant (β=0.387, p=0.318), and self-rated health was essentially unrelated to willingness (β=−0.120, p=0.595), suggesting that, among non-users, general

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health status does not independently drive pre-adoption intentions once age and demographics are controlled. Gender was not a significant predictor (β=−0.226, p=0.486).

The gender null is consistent with the broader elderly technology adoption literature, which has found that gender differences in technology acceptance are smaller among older cohorts than among younger populations (Morris & Venkatesh, 2000). Both elderly men and women in Macau had limited exposure to digital technology during their working lives, producing symmetrical inexperience and symmetrical adoption attitudes. The health-monitoring context—blood pressure monitors, glucose meters, and similar devices perceived as gender-neutral health tools rather than consumer electronics—may further attenuate gender differences.

5.1.2 Model M2: Adding TAM Constructs

Table 5.2. Model M2: Ordered Logit — Adding PU and PEOU

Variable	β	SE	z	p
Social Isolation (S)	-0.319	(0.175)	-1.822	0.068+
ln PU	0.162	(0.988)	0.164	0.870
ln PEOU	-0.593	(0.763)	-0.777	0.437
Age (per decade)	-1.238	(0.239)	-5.182	<0.001***
Male	-0.280	(0.335)	-0.837	0.403
Education (per 10 yrs)	0.529	(0.460)	1.150	0.250
Self-Rated Health	-0.074	(0.226)	-0.328	0.743
Cut point 1 (τ1)	-14.078	—	—	—
Cut point 2 (τ2)	-11.692	—	—	—
Cut point 3 (τ3)	-9.063	—	—	—
Cut point 4 (τ4)	-7.804	—	—	—
N	221			
Log-likelihood	-265.81			
AIC	553.62			
Pseudo-R^2	0.075			

Note. N=221. Log-likelihood = −265.81. Pseudo-R^2=0.075. AIC = 553.62. LR vs. M1: $\chi^2(2)$=0.98, p=0.613. Robust standard errors in parentheses.

The addition of ln PU and ln PEOU produced a negligible improvement in model fit (ΔLL=0.49, LR $\chi^2(2)$=0.98, p=0.613). Neither coefficient reached significance: ln PU was positive but small (β=0.162, SE=0.988, p=0.870), while ln PEOU was unexpectedly negative (β=−0.593, SE=0.763, p=0.437). The S coefficient remained essentially unchanged at −0.319 (p=0.068), confirming that the TAM constructs did not mediate the isolation effect. AIC actually increased from 550.61 (M1) to 553.62 (M2), indicating that the two added variables did not earn their keep in parsimony-adjusted fit. Because M2 excludes the TAcc composite, ln PU and ln PEOU are not subject to the

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severe multicollinearity that affects M3–M4; their coefficients are individually interpretable, and both are non-significant, contrary to the classical TAM expectation.

This pattern—insignificant TAM coefficients in the presence of demographic controls—challenges the standard TAM prediction that technology attitudes are the primary proximal determinants of adoption intention. For this sample of elderly non-users, attitudinal evaluations appear to be less predictive of adoption willingness than structural factors such as age and, as we shall see, the interaction between isolation and training access. One interpretation is that for digitally disadvantaged populations, the pathway from attitudes to intentions is disrupted by capability constraints: even respondents who evaluated the technology positively could not translate these positive evaluations into firm adoption intentions because they lacked the practical means to realize them.

5.1.3 Model M3: Adding the Technology Acceptance Composite

Table 5.3. Model M3: Ordered Logit — Adding TAcc Composite and TAnx

Variable	β	SE	z	p
Social Isolation (S)	-0.316	(0.171)	-1.848	0.065+
ln PU	-0.034	(2.317)	-0.015	0.988
ln PEOU	-1.095	(1.972)	-0.555	0.579
TAcc	0.240	(1.175)	0.204	0.838
TAnx	-0.227	(0.209)	-1.086	0.277
Age (per decade)	-1.162	(0.269)	-4.324	<0.001***
Male	-0.315	(0.345)	-0.913	0.361
Education (per 10 yrs)	0.576	(0.444)	1.296	0.195
Self-Rated Health	-0.065	(0.221)	-0.295	0.768
Cut point 1 (τ1)	-14.290	—	—	—
Cut point 2 (τ2)	-11.908	—	—	—
Cut point 3 (τ3)	-9.281	—	—	—
Cut point 4 (τ4)	-8.011	—	—	—
N	221			
Log-likelihood	-265.11			
AIC	556.22			
Pseudo-R^2	0.077			

Note. N=221. Log-likelihood = −265.11. Pseudo-R^2=0.077. AIC = 556.22. LR vs. M2: $\chi^2(2)=1.40$, p=0.498. TAnx = technology anxiety (Q26–Q28, corresponds to H4); TAcc = composite PU & PEOU index. Because TAcc is a linear combination of PU and PEOU, the three variables are highly collinear (VIFs 8–26); coefficients for ln PU, ln PEOU, and TAcc should be interpreted jointly, not individually. Robust standard errors in parentheses.

The joint addition of TAcc and TAnx did not meaningfully improve model fit (LR $\chi^2(2)=1.40$, p=0.498; AIC increased from 553.62 to 556.22). The TAcc coefficient was positive but small and

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non-significant (β=0.240, SE=1.175, p=0.838), and its sign is unstable across the M3/M4 block due to collinearity with ln PU and ln PEOU. The two TAM coefficients also shift relative to M2 (ln PU: 0.162→−0.034; ln PEOU: −0.593→−1.095), with substantially inflated standard errors, a textbook multicollinearity signature.

The theoretical predictor for Hypothesis 4, TAnx (technology anxiety, Q26–Q28), exhibits β=−0.227, SE=0.209, z=−1.09, p=0.277 in M3. The negative sign is consistent with the cost-function prediction that higher technology anxiety lowers latent adoption propensity, but the coefficient does not reach significance in M3. As shown below, TAnx strengthens in M4 once training and its interaction with S are accounted for, reaching marginal significance (β=−0.350, p=0.097).

5.1.4 Model M4: The Core Interaction — Social Isolation × Training

Table 5.4 presents the results for Model M4, the central model of the empirical analysis. This model adds $training$ and the interaction term $S \times training$ to the M3 specification.

Table 5.4. Model M4 (Core Model): Ordered Logit — Social Isolation × Training

Variable	β	SE	z	p
Social Isolation (S)	-0.189	(0.192)	-0.985	0.325
ln PU	-0.385	(2.046)	-0.188	0.851
ln PEOU	-1.388	(1.730)	-0.802	0.422
TAcc	0.295	(1.021)	0.289	0.773
TAnx	-0.350	(0.211)	-1.658	0.097+
Training	-0.540	(0.474)	-1.139	0.255
S × Training	-1.110	(0.625)	-1.776	0.076+
Age (per decade)	-1.047	(0.272)	-3.845	<0.001***
Male	-0.332	(0.350)	-0.948	0.343
Education (per 10 yrs)	0.760	(0.451)	1.685	0.092+
Self-Rated Health	-0.032	(0.228)	-0.141	0.888
Cut point 1 (τ1)	-14.413	—	—	—
Cut point 2 (τ2)	-12.015	—	—	—
Cut point 3 (τ3)	-9.326	—	—	—
Cut point 4 (τ4)	-8.021	—	—	—
N	221			
Log-likelihood	-261.35			
AIC	552.70			
Pseudo-R^2	0.090			

Note. N=221. Log-likelihood = −261.35. Pseudo-R^2=0.090. AIC = 552.70. LR test vs. M3: $\chi^2(2)$=7.52, p=0.023. †p<0.10, *p<0.05, **p<0.01, ***p<0.001. Robust standard errors in parentheses. The multicollinearity caution for ln PU, ln PEOU, and TAcc applies here as well.

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The interaction term S × Training carries a coefficient of −1.110 (SE=0.625, z=−1.78, p=0.076). This result is marginally significant at the 10% level—a conventional threshold in social science research where interaction effects are notoriously difficult to detect because the residual variance of a product term is inherently constrained by the marginal distributions of its components (McClelland & Judd, 1993; Aguinis et al., 2001). The likelihood ratio test comparing M4 to M3 is significant at conventional levels ($\chi^2(2)=7.52$, p=0.023), and the AIC decreases from 556.22 (M3) to 552.70 (M4), confirming that the joint addition of training and its interaction with S improves parsimony-adjusted fit despite the borderline coefficient p-value.

The negative sign confirms the theoretical prediction: when isolated elderly non-users receive training, the adoption-willingness benefit that accrues to non-isolated trained individuals is attenuated—and, in the predicted-probability analysis below, actually reverses for the most isolated subgroup. Because S is standardized and training is binary, the coefficient indicates that, conditional on training, a one-SD increase in S is associated with an additional 1.11-unit decrement in latent logit propensity relative to the same S contrast among the untrained. The direction is consistent with the technology-support mechanism: isolated elderly lack the family-based technical scaffolding that allows non-isolated individuals to convert classroom training into effective, confident technology appropriation.

The main effect of S in M4 (β=−0.189, p=0.325) is smaller in magnitude than in M1 (β=−0.308, p=0.077). This attenuation occurs because the interaction term absorbs the variance in S that is conditional on training status: in M4, the S coefficient represents the effect of isolation when training=0 (the reference group), whereas in M1 it averages over both trained and untrained respondents. Importantly, the M4 main effect remains negative, so even untrained isolated non-users show a (non-significant) tendency toward lower willingness. TAnx strengthens to β=−0.350 (SE=0.211, p=0.097) in M4, providing marginal support for H4: higher technology anxiety is associated with lower adoption propensity once the conditioning role of training is accounted for.

Age remains a significant predictor (β=−1.047, SE=0.272, p<0.001), though its magnitude is attenuated relative to M1 (−1.229), suggesting that part of the age effect operates through the correlation between age and training access. Education becomes marginally positive in M4 (β=0.760, p=0.092), consistent with a capability interpretation in which formal schooling modestly supports adoption willingness once attitudes and training are accounted for. The individual coefficients on ln PU (β=−0.385, p=0.851), ln PEOU (β=−1.388, p=0.422), and TAcc (β=0.295, p=0.773) are not separately interpretable because of the severe multicollinearity documented in Section 4.5; their joint contribution is captured by the model fit progression rather than by

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individual signs. Training main effect is negative but non-significant (β=−0.540, p=0.255), and self-rated health remains null (β=−0.032, p=0.888).

5.2 Deep Analysis of the Interaction Effect

5.2.1 Substantive Interpretation of $S \times training$

The S × Training interaction is the empirical heart of this study's dual-mechanism thesis. Its negative coefficient means that the combination of high social isolation and training participation is associated with lower adoption willingness than additive main effects would predict. To make this concrete, consider four subpopulations defined by the cross-classification of isolation level (P25 versus P75 of S) and training status.

For non-isolated elderly (low S), training participation provides additional technical competence on top of the informal family support already available. These individuals benefit from a "double advantage": family-based scaffolding plus formal training. Their adoption willingness should be relatively high.

For isolated elderly without training (high S, no training), the absence of formal training is partially compensated by the general low-stakes context of the survey—respondents can express willingness without committing to actual adoption. Their adoption willingness reflects a baseline orientation.

For isolated elderly with training (high S, training), however, the formal training experience may paradoxically highlight the gap between classroom competence and independent home use. Training in a community center setting, with instructors present to provide assistance, creates a "scaffolded competence" that does not transfer to unsupervised home use. Isolated elderly who have experienced training may therefore become more aware of their limitations rather than more confident—a "consciousness of incapacity" effect. This mechanism explains why the interaction coefficient is not merely attenuating but strongly negative: training, for the isolated, may shift awareness of limitations rather than build genuine self-efficacy.

5.2.2 Predicted Probability Analysis

Predicted probabilities from M4 illuminate the interaction's practical magnitude. Table 5.5 presents predicted probabilities for four scenarios constructed by crossing isolation level (low vs. high) with training status.

Table 5.5. Predicted Probabilities from Model M4

Scenario	Pr(Y=1)	Pr(Y=2)	Pr(Y=3)	Pr(Y=4)	Pr(Y=5)
Low S (P25), No Training	0.006	0.056	0.365	0.268	0.305
Low S (P25), Training	0.004	0.038	0.297	0.271	0.390

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High S (P75), No Training	0.008	0.070	0.401	0.259	0.262
High S (P75), Training	0.022	0.156	0.510	0.188	0.124

The pattern is substantively meaningful. Among non-isolated non-users (low S), training raises the predicted probability of favorable willingness (Y=4 or Y=5) from 57.3% to 66.1%—a gain of 8.8 percentage points. This is the expected "double advantage" pattern: trained, socially supported elderly non-users express the highest adoption willingness in the sample.

Among isolated non-users (high S), by contrast, training produces the opposite effect: the predicted probability of favorable willingness falls from 52.1% to 31.2%—a decline of 20.9 percentage points. The probability of the highest willingness category (Y=5) drops from 26.2% to 12.4%, while the probability of the neutral category rises from 40.1% to 51.0%. This is not the 45-point collapse suggested by an earlier preliminary model on a smaller, differently scaled sample, but it remains a substantively large and theoretically coherent reversal. Training, which should in principle empower isolated elderly by providing technical skills, instead appears to suppress their willingness relative to isolated non-users who have not been trained.

This pattern demands explanation. We propose three non-mutually-exclusive interpretations:

First, the **awareness mechanism**: training makes isolated elderly more acutely aware of the gap between supervised classroom learning and independent home use. In a training class, an instructor is present to assist; at home, alone, there is no such backup. For socially integrated elderly, family members fill this gap; for isolated elderly, the contrast between training environment and home environment may be demoralizing.

Second, the selection mechanism: the 12 isolated non-users who participated in training may be a select group—those who sought training precisely because they experienced difficulties with technology or because community outreach targeted them. Their lower post-training willingness could reflect pre-existing frustration rather than a training-induced awareness effect. Without random assignment or pre-training measures of willingness, this selection account cannot be empirically disentangled from the awareness mechanism.

Third, the small-sample amplification mechanism: with only 12 observations in the high-S/training cell, the predicted probabilities for this group rest on a thin empirical base and are sensitive to influential cases. The 20.9-percentage-point decline should therefore be interpreted as a point estimate of a real conditional effect rather than a precisely measured population parameter; the LR test (p=0.023) indicates that the interaction block as a whole is informative, but the exact magnitude warrants replication with a larger trained subsample.

5.2.3 Observed Group Means: Empirical Validation

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To assess whether the predicted probabilities reflect actual patterns in the data, we examined observed group means using a dichotomized isolation variable with a threshold of S ≥ 0.30, which corresponds to the 75th percentile of the non-user S distribution (P75 = 0.302) and separates the most socially isolated quartile from the remainder. Table 5.6 presents the results. Cell sizes are uneven—twelve respondents fall into the high-isolation/trained cell, thirty-six into the high-isolation/untrained cell, eighteen into the low-isolation/trained cell, and 155 into the low-isolation/untrained cell—but the directional pattern is informative.

Table 5.6. Observed Adoption Willingness by Group (Non-users, Dichotomized S ≥ 0.30, N = 221)

Group	n	Mean willingness (1–5)	Proportion favorable (Y ≥ 4)
High isolation, received training	12	3.000	0.167
High isolation, no training	36	3.694	0.556
Low isolation, received training	18	3.833	0.611
Low isolation, no training	155	3.735	0.529

The observed data confirm the interaction pattern predicted by M4. High-isolation trained respondents (n = 12) had the lowest mean willingness (M = 3.00) and by far the lowest proportion of favorable responses (16.7%), whereas high-isolation respondents without training (n = 36) reported a mean of 3.69 with 55.6% favorable. The 39-percentage-point gap between trained and untrained high-isolation non-users runs in the same direction as the 20.9-point decline estimated from M4, although the observed gap is larger in magnitude—a discrepancy consistent with the model smoothing over the small, heterogeneous trained cell.

The twelve high-isolation trained individuals reported a mean willingness of exactly 3.00—at the neutral midpoint—with only 16.7% reaching a favorable response (compared with 55.6% of their untrained counterparts). While the small cell size (n = 12) cautions against precise inference, the qualitative picture is unambiguous: within the most isolated segment of the non-user population, those who had already attended a community training course were the least, not the most, willing to adopt the device. This observed pattern is not a model artifact; it survives in the raw cell means.

Among the low-isolation groups the effect reverses in direction but shrinks in magnitude: trained respondents reported a mean willingness of 3.83 and a 61.1% favorable rate, compared with 3.74 and 52.9% among untrained respondents. Training therefore accompanies a modest eight-point increase in favorability for socially integrated non-users, but a thirty-nine-point decrease for the most isolated. The interaction is not symmetric; it is concentrated almost entirely in the high-isolation tail, which is precisely where the policy stakes are highest.

5.3 Marginal Effects Analysis

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5.3.1 Average Marginal Effects from M4

To complement the coefficient-based interpretation, Table 5.7 reports average marginal effects (AMEs) from Model M4, computed by averaging dPr(Y=j)/dx over all observed covariate profiles. AMEs translate latent-variable coefficients into probability-scale effects for each outcome category. The S×training interaction AME is computed as the cross-partial derivative of each outcome probability with respect to S and training, averaged across observations.

Table 5.7. Average Marginal Effects from Model M4

Outcome	S	TAnx	S × Training
Y = 1 (most unwilling)	0.004 (0.003)	0.003 (0.003)	0.029 (0.022)
Y = 2	0.023* (0.012)	0.021+ (0.012)	0.064** (0.023)
Y = 3 (neutral)	0.041+ (0.024)	0.049 (0.030)	0.099+ (0.055)
Y = 4	−0.013+ (0.007)	−0.013 (0.009)	−0.024 (0.045)
Y = 5 (most willing)	−0.055+ (0.030)	−0.059+ (0.035)	−0.167 (0.114)

Note. TAnx = technology anxiety (Q26–Q28, corresponds to H4); TAcc = composite PU & PEOU index.

The AME of social isolation on the probability of the highest willingness category (Y=5) is −0.055 ($p<0.10$): a one-SD increase in S reduces the probability of "definitely would use" by about 5.5 percentage points, with a corresponding increase in the neutral category (Y=3) of 4.1 points. The TAnx AME on P(Y=3) is +0.049 (n.s.) and on P(Y=5) is −0.059 ($p<0.10$), providing probability-scale evidence consistent with H4: technology anxiety shifts respondents out of the highest willingness category toward neutrality. The S×training interaction AME is +6.4 points on P(Y=2) ($p<0.01$) and +9.9 points on P(Y=3) ($p<0.10$), with corresponding negative shifts at the favorable end; in substantive terms, training among high-S non-users shifts mass from favorable into neutral and mildly unfavorable categories.

These AME estimates are consistent with the coefficient-based picture: S and TAnx push respondents away from the highest willingness category, while the interaction with training shifts probability mass toward the neutral category among isolated non-users. The AMEs are modest in absolute magnitude—typically 5–10 percentage points per SD—but their direction is coherent across outcome categories and aligns with the predicted-probability analysis in Table 5.5.

These AME estimates, while derived from a model that does not include the interaction terms, provide a useful baseline: the isolation effect on the probability scale is meaningful in magnitude even though it falls short of conventional significance thresholds, consistent with the interpretation that its effect is heterogeneous (conditional on training status) rather than uniformly distributed across the sample.

5.4 Robustness Checks

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5.4.1 Binary Logit Specification

To assess the robustness of the interaction effect to alternative treatment of the dependent variable, we re-estimated M4 on N=221 non-users using a binary logit specification with favorable willingness (Q18 ≥ 4) as the outcome. Table 5.8 reports the results. TAcc was dropped from this specification because its variance inflation factor in the ordered model exceeds 25, producing near-singular information matrices on the binary outcome scale; ln PU, ln PEOU and TAnx are retained as the TAM and technology-anxiety controls.

Table 5.8. Binary Logit Robustness Check (Non-users, N = 221)

Variable	β	SE	z	p
S (social isolation)	−0.062	0.181	−0.34	0.731
Age (per decade)	−0.896	0.254	−3.53	<0.001***
Male	−0.520	0.367	−1.42	0.156
Education (per 10 yrs)	0.579	0.396	1.46	0.144
Self-rated health	−0.127	0.209	−0.61	0.543
ln PU	−0.109	0.804	−0.14	0.893
ln PEOU	−0.747	0.693	−1.08	0.281
TAnx	−0.524	0.232	−2.26	0.024*
Training	−0.906	0.476	−1.90	0.057†
S × Training	−1.085	0.540	−2.01	0.045*
Constant	9.522	2.031	4.69	<0.001***

Note. Binary logit re-estimated on N=221 non-users with the dependent variable recoded as 1 if Q18 ≥ 4 ("probably willing" or "definitely willing"), 0 otherwise. TAcc is omitted from this robustness specification because its VIF exceeds 25 in M4, producing near-singularity on the binary outcome scale; ln PU, ln PEOU and TAnx are retained as TAM/technology-anxiety controls. Robust standard errors in parentheses. † p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Log-likelihood = −133.96; McFadden pseudo-R^2 = 0.124.

The S × Training coefficient in the binary logit is negative and statistically significant (β = −1.085, SE = 0.540, p = 0.045), preserving both the sign and the inferential standing of the ordered-logit interaction (β = −1.110, p = 0.076). TAnx also retains its negative effect (β = −0.524, p = 0.024), and age remains a strong negative predictor (β = −0.896, p < 0.001). The interaction therefore does not depend on the ordered-logit cutpoint structure; it survives a more conservative binary recoding of the outcome.

5.4.2 Alternative Isolation Thresholds

The dichotomization at S ≥ 0.30 used in the group analysis (Table 5.6) was chosen to isolate the upper quartile of socially isolated non-users, where the interaction effect is concentrated. Analyses using alternative thresholds (median split at S ≈ −0.20, and a stricter cut at S ≥ 0.50) yield the same

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directional pattern; the magnitude of the training–isolation interaction attenuates as the threshold moves toward the median but remains negative in every specification we examined.

5.4.3 Sensitivity to Outlier Influence

The small high-S/training cell ($n = 12$) raises the possibility that a small number of influential observations drive the interaction effect. While formal influence diagnostics (e.g., DFbetas) are not straightforward to compute for ordered logit models, the consistency of results across the ordered logit, binary logit, and raw group means suggests that the interaction pattern is not solely attributable to a small number of extreme cases. Nevertheless, the caveat that small-cell results require replication with larger samples is essential.

5.4.4 The Gender Null: Confirming Prior Expectations

Gender (male = 1) is consistently insignificant across all non-user specifications, with coefficients ranging from $\beta = -0.226$ (M1) to $\beta = -0.332$ (M4), all with $p > 0.30$. This null result is consistent with the broader elderly technology adoption literature, which frequently reports no direct gender effect once age, education and prior technology exposure are controlled.

An alternative explanation invokes the health monitoring context: blood pressure monitors, glucose meters, and similar health devices are perceived as gender-neutral health tools rather than as "technology" in the consumer electronics sense. If both men and women evaluate health monitoring devices through a health lens rather than a technology lens, gender differences in technology anxiety or interest would not manifest.

5.4.5 Model Fit Comparison Across Specifications

A systematic comparison of model fit statistics across the four specifications reveals the expected progression. The baseline M1 (LL=−266.30, pseudo-R^2=0.073, AIC=550.61) achieves its explanatory power primarily through age. Adding ln PU and ln PEOU in M2 produces essentially no improvement (LL=−265.81, AIC=553.62; LR $\chi^2(2)=0.98$, $p=0.613$), and adding TAcc and TAnx in M3 produces a similarly negligible gain (LL=−265.11, AIC=556.22; LR $\chi^2(2)=1.40$, $p=0.498$). AIC actually rises across M2 and M3 because the penalty for additional parameters exceeds the modest log-likelihood improvement—direct evidence that, for non-users, attitudinal variables do not enhance parsimony-adjusted fit.

The critical improvement comes with M4 (LL=−261.35, pseudo-R^2=0.090, AIC=552.70), which achieves the highest log-likelihood and the lowest AIC of the four specifications. The LR test comparing M4 to M3 ($\chi^2(2)=7.52$, $p=0.023$) confirms that adding training and its interaction with S significantly improves fit despite the interaction coefficient's borderline p-value. The pattern

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indicates that the explanatory power of social context for non-user willingness lies not in attitudinal mediation but in the conditional (interaction) effect of training access.

Table 5.9. Model Fit Comparison Summary

Model	Log-lik.	Pseudo-R^2	AIC	LR test vs. predecessor
M1 (S + controls)	−266.30	0.073	550.61	—
M2 (+ lnPU, lnPEOU)	−265.81	0.075	553.62	$\chi^2(2)=0.98$, p=0.613
M3 (+ TAcc, TAnx)	−265.11	0.077	556.22	$\chi^2(2)=1.40$, p=0.498
M4 (+ training, S×training)	−261.35	0.090	552.70	$\chi^2(2)=7.52$, p=0.023*

The pattern is clear: M4 is the best-fitting model by both log-likelihood and AIC, and its improvement over M3 is driven primarily by the S×training interaction rather than by the training main effect. This anchors the study's central claim that the interaction between social isolation and training access is the key mechanism shaping adoption willingness among elderly non-users—with the important caveat that, for non-users, the interaction operates in the counterintuitive (negative) direction.

5.5 Summary of Hypothesis Tests

Table 5.10 consolidates the hypothesis test results.

Table 5.10. Hypothesis Test Summary

Hyp.	Prediction	Non-user result (N=221)	Status	Current user result (N=279)
H1	S negative main effect on Y	β=−0.189, p=0.325 (M4); β=−0.308, p=0.077 (M1)	Partially marginally supported	β=−0.423, p=0.074 (M4)
H2	ln PU positive effect on Y	β=−0.385, p=0.851 (M4)	Not supported	β=−5.680, p<0.001 (M4)†
H3	ln PEOU positive effect on Y	β=−1.388, p=0.422 (M4)	Not supported	β=−5.886, p<0.001 (M4)†
H4	TAnx negative association with Y	β=−0.350, p=0.097 (M4)	Marginally supported	β=−0.407, p=0.050 (M4)
H5	S×training negative effect	β=−1.110, p=0.076 (M4); LR $\chi^2(2)=7.52$, p=0.023	Marginally supported	β=+0.758, p=0.043 (M4)‡

Note. † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. In M3–M4, lnPU, lnPEOU, and TAcc exhibit severe multicollinearity (VIF up to 26.2); individual coefficients are unstable and should not be interpreted in isolation—joint significance and model fit are the relevant criteria. M2, which excludes TAcc, does not suffer from this problem; its TAM coefficients are individually interpretable, and both are non-significant. ‡ The S×training interaction reverses sign in the user group: among current users, training is associated with higher satisfaction among the socially isolated, the opposite of the pattern observed for non-users.

The pattern of results reveals a clear hierarchy of empirical support. The traditional TAM hypotheses H2 and H3 are uniformly unsupported among non-users: ln PU (β=−0.385, p=0.851) and ln PEOU (β=−1.388, p=0.422) do not significantly predict adoption willingness in M4,

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although their joint contribution in M3/M4 is confounded by collinearity with TAcc. The main effect of social isolation (H1) shows no stable global effect: it is marginally negative in the baseline M1 (p = 0.077) but loses significance once the training interaction enters M4, indicating conditional heterogeneity rather than a uniform main effect.189, p=0.325), though it is marginally negative in M1 (β=−0.308, p=0.077), consistent with the theoretical prediction that opposing mechanisms largely cancel at the population level. H4 (technology anxiety) receives marginal support in M4 (β=−0.350, p=0.097), with the expected negative sign. H5, the core interaction hypothesis, receives marginal support in the ordered logit (β=−1.110, p=0.076) and is supported by the LR test of M4 versus M3 ($\chi^2(2)=7.52$, p=0.023). The "Current User Result" column reports parallel estimates from the current-user subsample (Section 5.6).

5.6 Current User Subgroup Regression Analysis

5.6.1 Hierarchical Regression Results for Current Users

Tables 5.11–5.14 report the M1–M4 ordered logit estimates for the current-user subsample (N=279), using overall post-use satisfaction (Y_user, Q14) as the dependent variable. The same hierarchical specification sequence is followed, permitting direct comparison with the non-user results.

Table 5.11. Model M1 (Users): Ordered Logit — Sustained Usage Satisfaction

Variable	β	SE	z	p
Social Isolation (S)	-0.207	(0.176)	-1.174	0.240
Age (per decade)	-0.060	(0.202)	-0.297	0.767
Male	0.978	(0.241)	4.058	<0.001***
Education (per 10 yrs)	0.191	(0.321)	0.595	0.552
Self-Rated Health	-0.119	(0.184)	-0.647	0.518
Cut point 1 (τ1)	-4.835	—	—	—
Cut point 2 (τ2)	-2.368	—	—	—
Cut point 3 (τ3)	-0.755	—	—	—
Cut point 4 (τ4)	1.191	—	—	—
N	279			
Log-likelihood	-358.46			
AIC	734.91			
Pseudo-R^2	0.030			

Among current users, the social isolation coefficient is negative but not significant in M1 (β=−0.207, SE=0.176, p=0.240). Age is also non-significant (β=−0.060, p=0.767)—a striking contrast with non-users, among whom age was the dominant predictor. Gender, by contrast, emerges as a strong predictor: male users report significantly higher satisfaction than female users

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(β=0.978, SE=0.241, p<0.001), a pattern that persists across all four specifications. The user M1 pseudo-R^2 is only 0.030, indicating that demographics alone explain little variation in post-use satisfaction.

Table 5.12. Model M2 (Users): Ordered Logit — Adding PU and PEOU

Variable	β	SE	z	p
Social Isolation (S)	-0.265	(0.178)	-1.490	0.136
ln PU	-1.250	(0.538)	-2.322	0.020*
ln PEOU	-0.357	(0.580)	-0.615	0.539
Age (per decade)	0.033	(0.218)	0.151	0.880
Male	0.870	(0.259)	3.361	0.001**
Education (per 10 yrs)	0.642	(0.365)	1.760	0.078+
Self-Rated Health	-0.047	(0.211)	-0.222	0.824
Cut point 1 (τ1)	-5.447	—	—	—
Cut point 2 (τ2)	-2.960	—	—	—
Cut point 3 (τ3)	-1.330	—	—	—
Cut point 4 (τ4)	0.685	—	—	—
N	279			
Log-likelihood	-352.01			
AIC	726.01			
Pseudo-R^2	0.047			

In M2, ln PU enters with a significant negative coefficient (β=−1.250, SE=0.538, p=0.020) while ln PEOU is non-significant (β=−0.357, p=0.539). The negative PU sign in the user group is counterintuitive in isolation but should not be over-interpreted: as in the non-user case, M3 introduces TAcc, which is highly collinear with both ln PU and ln PEU (r=0.893 and 0.902 respectively), and the individual coefficients shift sharply as a result. Model fit improves modestly in M2 (AIC falls from 734.91 to 726.01).

Table 5.13. Model M3 (Users): Ordered Logit — Adding TAcc and TAnx

Variable	β	SE	z	p
Social Isolation (S)	-0.076	(0.189)	-0.403	0.687
ln PU	-5.583	(1.423)	-3.924	<0.001***
ln PEOU	-5.676	(1.442)	-3.937	<0.001***
TAcc	3.854	(0.872)	4.421	<0.001***
TAnx	-0.582	(0.200)	-2.912	0.004**
Age (per decade)	-0.070	(0.215)	-0.326	0.744
Male	0.798	(0.270)	2.957	0.003**
Education (per 10 yrs)	0.621	(0.403)	1.542	0.123

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Self-Rated Health	-0.124	(0.238)	-0.521	0.602
Cut point 1 (τ1)	-6.738	—	—	—
Cut point 2 (τ2)	-4.268	—	—	—
Cut point 3 (τ3)	-2.571	—	—	—
Cut point 4 (τ4)	-0.214	—	—	—
N	279			
Log-likelihood	-325.47			
AIC	676.95			
Pseudo-R^2	0.119			

In M3, TAcc enters with a large positive coefficient (β=3.854, SE=0.872, p<0.001), while ln PU (β=−5.583) and ln PEOU (β=−5.676) carry large negative coefficients with inflated standard errors—classic suppression produced by the collinearity among the three attitudinal variables (VIFs 6.5–17.3). The interpretable signal from this block is jointly positive: users with more favorable technology attitudes report substantially higher satisfaction, as reflected in the large likelihood improvement (LL from −352.01 to −325.47; AIC from 726.01 to 676.95; LR $\chi^2(2)=53.07$, p<0.001). TAnx enters with the expected negative sign (β=−0.582, SE=0.200, p=0.004), providing stronger support for H4 among users than among non-users.

Table 5.14. Model M4 (Users): Ordered Logit — Social Isolation × Training

Variable	β	SE	z	p
Social Isolation (S)	-0.423	(0.237)	-1.784	0.074+
ln PU	-5.680	(1.202)	-4.725	<0.001***
ln PEOU	-5.886	(1.389)	-4.237	<0.001***
TAcc	4.131	(0.814)	5.073	<0.001***
TAnx	-0.407	(0.208)	-1.957	0.050+
Training	1.158	(0.277)	4.182	<0.001***
S × Training	0.758	(0.375)	2.020	0.043*
Age (per decade)	-0.084	(0.217)	-0.388	0.698
Male	0.677	(0.284)	2.384	0.017*
Education (per 10 yrs)	0.666	(0.391)	1.703	0.089+
Self-Rated Health	-0.165	(0.236)	-0.699	0.485
Cut point 1 (τ1)	-5.513	—	—	—
Cut point 2 (τ2)	-3.023	—	—	—
Cut point 3 (τ3)	-1.207	—	—	—
Cut point 4 (τ4)	1.362	—	—	—
N	279			
Log-likelihood	-310.35			
AIC	650.69			

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Pseudo-R^2	0.160

The S×training interaction among users is positive and significant (β=+0.758, SE=0.375, z=2.02, p=0.043), with a large positive training main effect (β=1.158, SE=0.277, p<0.001). This is the opposite sign from the non-user interaction: among current users, training is associated with higher satisfaction, and the benefit is larger for the socially isolated. The S main effect becomes more negative and marginally significant in M4 (β=−0.423, p=0.074), while TAnx retains its negative association (β=−0.407, p=0.050). Model fit improves substantially (LL=−310.35, AIC=650.69, pseudo-R^2=0.160; LR $\chi^2(2)$=30.26, p<0.001 versus M3), and M4 is the best-fitting user specification across all criteria.

5.6.2 Interaction Effect: Cross-Group Comparison

Table 5.15 presents predicted satisfaction probabilities for four user subgroups (low/high S × trained/untrained), mirroring the non-user analysis in Table 5.5. Among non-isolated users (low S), training raises the probability of favorable satisfaction (Y=4 or Y=5) from 56.8% to 75.0%. Among isolated users (high S), training raises favorable satisfaction from 47.8% to 80.3%—a larger gain of 32.5 percentage points. This is the mirror image of the non-user pattern: for people who have already crossed the adoption threshold, formal training functions as an empowerment mechanism, and its benefits are greatest for those who lack informal family support.

Table 5.15. Predicted Sustained Usage Satisfaction by Group (Users)

Scenario	Pr(Y=1)	Pr(Y=2)	Pr(Y=3)	Pr(Y=4)	Pr(Y=5)
Low S (P25), No Training	0.013	0.116	0.303	0.421	0.147
Low S (P25), Training	0.005	0.052	0.193	0.491	0.259
High S (P75), No Training	0.020	0.162	0.341	0.367	0.111
High S (P75), Training	0.004	0.038	0.155	0.490	0.313

5.6.3 Cross-Sample Comparative Discussion

A direct comparison of coefficients across the two subsamples reveals both commonalities and a sharp divergence in the central interaction. The social isolation main effect is negative in both groups but only marginally significant in M4 (non-user β=−0.189, p=0.325; user β=−0.423, p=0.074). TAnx carries the expected negative sign in both groups, with stronger evidence among users (non-user β=−0.350, p=0.097; user β=−0.407, p=0.050). The critical divergence is the S×training interaction: negative and marginally significant among non-users (β=−1.110, p=0.076), positive and significant among users (β=+0.758, p=0.043). The unified cost-benefit framework in Chapter 3 interprets this sign reversal as reflecting different cost-benefit trade-offs at different

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stages of the adoption journey. For non-users weighing prospective adoption, training may surface awareness of the gap between supervised learning and unsupervised home use—particularly for those without family scaffolding—which raises anticipated cost and suppresses willingness. For users already operating the device at home, training reduces ongoing operational friction, and the reduction is most consequential for isolated users who cannot rely on family assistance. The same structural variable (training access) thus operates on opposite sides of the cost-benefit ledger depending on adoption stage, a finding with direct implications for the design of digital-inclusion policy.

5.7 Discussion

5.7.1 The Primacy of the Technology Support Channel

The non-user analysis identifies the technology-support channel as the primary pathway through which isolation affects willingness. The marginally significant S×training interaction ($\beta = -1.110$, $p = 0.076$; LR $\chi^2(2) = 7.52$, $p = 0.023$) demonstrates that isolation's effect is conditional on formal technical support—and the conditioning runs negative for non-users: isolated elderly who receive training do not become empowered adopters; their predicted favorable-willingness probability drops by 20.9 percentage points relative to isolated non-users without training.

Two parallel explanations can account for this negative interaction. The first is a cognitive-gap mechanism: the contrast between supervised classroom assistance and the unsupported home environment may generate learned incapacity, suppressing willingness below even the baseline of untrained isolated non-users. The second is self-selection: elderly who already experience greater technological difficulty or higher isolation may be the most likely to seek training, and their lower baseline willingness reflects pre-existing difficulty rather than a causal training effect. The cross-sectional design cannot disentangle the two; longitudinal or experimental designs are needed.

The policy implication is not that training should be withheld—training is essential—but that pre-adoption programs for isolated elderly need a bridge component: in-home follow-up, peer mentoring, and simplified interfaces that reduce the competence threshold for independent use.

5.7.2 The Attitudinal Paradox: Why TAM Fails for Elderly Non-Users

The consistent non-significance—and in some cases wrong-signed coefficients—of TAM constructs among non-users challenges the standard acceptance framework. In the broader TAM literature, perceived usefulness and ease of use reliably predict adoption intentions; they do not here.$PUPEOU$

We propose that this failure reflects an asymmetry between technology-experienced and technology-naive populations. Among experienced users, attitudes are informed by direct use and

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therefore predict behavior. Among non-users, attitudes are hypothetical—beliefs about a device never operated, formed in the abstract context of a survey interview—and may bear little relation to the actual adoption decision, which turns on concrete considerations of capability, effort, and social support that generic Likert items do not capture. The predictive power of TAM variables therefore has a clear boundary condition: non-users without direct device experience hold only abstract technological beliefs, rendering PU and PEOU non-predictive, whereas current users with hands-on experience produce attitudinal constructs that significantly explain satisfaction.

This interpretation extends the intention-behavior gap literature (Sheeran, 2002) by suggesting the gap is particularly wide for elderly evaluating unfamiliar health technologies. Future studies of elderly adoption should de-emphasize generic attitudinal predictors and focus on capability-based constructs (digital self-efficacy, perceived behavioral control) and social-context variables (isolation, training access, family support), while treating technology anxiety as a distinct cost-side construct rather than pooling it with usefulness and ease of use.

5.7.3 Age as the Structural Determinant

Age is the most robust predictor of non-user willingness ($\beta \approx -1.0$ to -1.2 per decade, $p < 0.001$ across M1–M4): each additional decade reduces latent adoption propensity by roughly one logit unit. Among current users, by contrast, age is non-significant in every specification ($\beta \approx -0.06$ to -0.08, $p > 0.69$), suggesting the age gradient operates at the adoption threshold rather than in post-use satisfaction. This contrast may also reflect survivor-selection bias: elderly who struggle most with digital interfaces are more likely to discontinue use, so those who remain—particularly the oldest users—are disproportionately those with stronger intrinsic digital adaptability, attenuating the observed age gradient on satisfaction.

5.7.4 Implications for the Digital Divide Literature

These results add a fourth dimension—psychological readiness for independent use—to the established digital-divide framework of access, skills, and outcomes; training without a bridge to independent home use may widen this psychological dimension for the isolated.

5.7.5 Comparing Effect Sizes: Age, Isolation, and Training

Among non-users, age dominates: the 65-to-80 gap spans roughly 1.57 logit units, dwarfing the S main effect (-0.189) and comparable to the conditional S×training interaction (-1.110). The interaction matters not for population-level magnitude but for mechanism: isolation's effect depends on formal technical support, and that channel is actionable in ways age is not. Among users, gender ($\beta = 0.677$) and training ($\beta = 1.158$) replace age as the dominant structural predictors, and the interaction reverses sign.

5.7.6 Toward a Contingent Theory of Elderly Technology Adoption

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The pattern of null main effects and conditional interaction supports a contingent theory of elderly adoption: willingness is driven less by attitudinal evaluations than by capability constraints and social context. The Chapter 3 cost-benefit framework provides the architecture: isolation changes the feasibility set rather than preferences, and the technology-support channel operates on the feasibility side. For digitally disadvantaged populations, a capability approach (Sen, 1999; Robeyns, 2017) offers more purchase than attitude-driven models such as TAM or TPB.

5.7.7 Scope Conditions and Boundary Conditions

Generalizability is bounded by four conditions: the cross-sectional design precludes causal claims; Macau's subsidized, high-density context may not generalize to low-resource settings; omitted variables and reverse causality may bias estimates; and the small trained non-user cell limits interaction precision. Longitudinal or experimental designs are the natural next step. Despite these limits, the study demonstrates that isolation affects adoption through opposing channels, with the technology-support channel dominating.

Practical implications stemming from these findings, together with methodological limitations and directions for future inquiry, are addressed in Chapter 6.

Chapter 6: Conclusion

6.1 Main Findings

This study examined the determinants of older adults' willingness to adopt AI-enabled remote health-monitoring devices in Macao within a unified cost–benefit utility framework. Building on the theoretical model developed in Chapter 3, the empirical analysis distinguished two groups: non-users (future adoption intention under free or heavily subsidised conditions) and current users (post-use satisfaction). The central research questions concerned the dual role of social isolation, the moderating effect of digital training, the predictive power of the classic TAM constructs, and the independent contribution of technology anxiety.

First, the main effect of social isolation on adoption intention was statistically insignificant in most specifications (Hypothesis H1). Raw descriptive statistics initially suggested higher willingness among those living alone, yet this association disappeared after controlling for digital training and demographic characteristics. This pattern is consistent with the dual-mechanism argument advanced in Chapter 2 and formalised in Chapter 3: social isolation simultaneously raises the perceived benefit of remote monitoring (compensatory need when informal care is scarce) and raises the perceived cost (absence of informal technical support). The two opposing channels largely offset each other, producing a near-zero net effect.

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Second, the interaction between social isolation and digital training exhibited a clear sign reversal across the two subsamples—the most distinctive empirical result of the study. Among non-users, the interaction term was negative: participation in digital training was associated with lower, rather than higher, adoption intention among more socially isolated older adults. One plausible interpretation is that classroom training, when not followed by continued in-home support, makes highly isolated non-users more acutely aware of the gap between supervised learning and independent use, thereby reducing further willingness to try. Among current users, by contrast, the same interaction was positive: digital training was associated with substantially higher post-use satisfaction. Thus, the same formal training that appears counterproductive for isolated non-users becomes beneficial once the device has already been adopted and some operational experience has been gained.

Third, the classic Technology Acceptance Model constructs—perceived usefulness (PU) and perceived ease of use (PEOU)—showed weak or non-significant associations with adoption intention among non-users (Hypotheses H2 and H3). This finding is consistent with the boundary condition noted in Chapter 2: for individuals who have never used the technology, PU and PEOU are largely abstract beliefs rather than experience-based evaluations, and therefore lose predictive power. Technology anxiety (TAnx), by contrast, retained a negative association in several specifications (Hypothesis H4), underscoring that affective barriers remain relevant even when cognitive evaluations of usefulness and ease of use do not.

Fourth, descriptive statistics show that smartphone ownership among Macao older adults is already very high. Ownership itself, however, does not automatically translate into willingness to use health-monitoring functions. Given near-saturation penetration in this population, smartphone ownership is treated only as contextual background rather than a core regression predictor. Formal digital-training participation, by contrast, exhibits meaningful conditional associations with adoption-related outcomes, subject to the moderating role of social isolation.

Taken together, the results indicate that structural and support-related factors—particularly the interplay between social isolation and the availability of sustained technical assistance—play a more decisive role than pure attitudinal evaluations for the non-user population, while the same support factors continue to shape satisfaction once the device has been adopted.

6.2 Practical Implications

Individual-and-family level

The empirical finding that classroom-only training can reduce adoption willingness among highly isolated non-users carries a direct implication for families. Demonstration without subsequent

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in-home support risks heightening rather than reducing technology anxiety. Families should therefore treat the initial introduction of an AI-enabled remote health-monitoring device as the beginning of a longer support process rather than a one-off event.

Concrete steps include: pairing any formal training session with immediate follow-up practice at home under the guidance of a younger family member; preparing simple, printed step-by-step guides or annotated screenshots that the older adult can consult independently; and activating the device's remote-guardianship functions so that family members receive alerts and can provide timely assistance. Sustained informal support from co-resident or nearby relatives remains the most reliable buffer against the operational difficulties that formal training alone cannot fully resolve.

Community-service level

Community organisations, particularly those already operating smart-health projects such as the Macao Federation of Trade Unions (MFTU), are well positioned to address the sign-reversal pattern observed in the data. Training programmes should be redesigned along two distinct tracks.

For non-users—especially those living alone or with limited family contact—training must be accompanied by scheduled post-training home visits or volunteer follow-up. Isolated older adults who attend a classroom session but then return to an unsupported home environment are precisely the group for whom training appears to lower subsequent willingness. For current users, the same training resources can be used to consolidate operational skills and raise satisfaction, as the positive interaction observed among users demonstrates.

In practical terms, communities should: maintain a simple register of high-isolation older adults who have received training; assign community workers or trained volunteers to conduct at least one follow-up visit within two weeks; and shift the evaluation metric of training programmes from "number of participants" to "proportion of participants who continue independent use after three months."

Governmental level

Policy-making should move beyond one-off hardware or classroom-training investments and build sustained support infrastructure to match the conditional effects uncovered in this study. At the policy level, the results suggest that simply expanding device distribution or organising large-scale classroom training is insufficient. Because the net effect of social isolation is close to zero and the effect of training is highly conditional on subsequent support, public resources should prioritise the creation of continuous support chains rather than one-off interventions.

Recommended actions include: integrating AI-enabled remote health-monitoring devices into existing community eldercare platforms with mandatory post-installation follow-up protocols;

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developing a multi-tier early-warning system that routes device alerts not only to family members but also to community service providers when family support is absent; and commissioning longitudinal evaluations that track both adoption and sustained use, with particular attention to the high-isolation subgroup. Public communication campaigns should emphasise practical help-seeking channels and the availability of ongoing assistance, rather than focusing solely on the abstract benefits of the technology.

6.3 Limitations and Directions for Future Research

This study relies on cross-sectional survey data and can therefore capture only conditional associations at a single point in time. It cannot observe changes after device distribution or training, nor can it fully rule out reverse causality.

Several analytical constraints should be acknowledged. First, the proportional odds assumption was modestly violated for age and the S\times training interaction term in ordered-logit estimation. Although generalized ordered-logit robustness checks yielded substantively consistent conclusions, mild assumption violations remain a caveat for interpretation. Second, among non-users the subsample of highly socially isolated older adults who had received digital training is small (n=12), which reduces the precision of the interaction-term estimate and warrants caution when interpreting effect magnitude, even though raw cell means and binary-logit robustness support the core directional finding. Third, future adoption intention was elicited from non-users under “free or heavily subsidised” conditions and may not fully represent choices under realistic pricing or service arrangements. Fourth, social isolation was operationalised as a simplified index based on living arrangement and contact frequency rather than the full Lubben Social Network Scale (LSNS-6). Fifth, the weak predictive performance of classic TAM constructs among non-users is bounded by measurement conditions: perceptions formed without hands-on device experience may lack predictive validity for behavioural intentions. In addition, the Macao-specific sample context limits direct generalisation to other regional settings.

Future adoption-intention work could productively address these constraints by oversampling highly isolated older adults who receive training and collecting longitudinal panel data. Collecting objective device-usage logs in addition to self-reported intention and satisfaction would enrich evidence beyond survey-based responses. Incorporating the perspectives and support behaviours of family members also helps unpack household-level decision-making processes. It would also be valuable to test whether training programmes that embed mandatory post-session home support reverse the negative interaction observed among non-users in the present data. Bayesian estimation with weakly informative priors could also be considered for future studies dealing with small analytical cells.

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