Why Older Adults Avoid Health Information: A Meta-Analytic Structural Equation Modeling Study

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Abstract

This study adopted Meta-Analytic Structural Equation Modeling (MASEM) to synthesize findings from 15 empirical studies involving 11,472 older adults, systematically examining the mechanisms underpinning health information avoidance among this demographic. The results indicated that: (1) both perceived hazard characteristics and negative information characteristics are significantly and positively related to health information avoidance; (2) affective risk response mediates the relationship between perceived hazard characteristics and health information avoidance; and (3) demographic factors such as older age, lower education attainment, and Chinese cultural background reinforce the effects of information characteristics on avoidance behavior, whilst gender exhibits differentiated moderating effects across different pathways. This study elucidates the integrated mechanisms of health information avoidance among older adults and offers evidence-based implications for precise health communication.

***Keywords*:** Older adults, Health information avoidance, Meta-Analytic Structural Equation Modeling (MASEM), Perceived hazard characteristics, Negative information characteristics

Introduction

According to the United Nations' World Population Prospects 2022, the global proportion of individuals aged 65 and older is expected to increase from 10% in 2022 to 16% by 2050 (United Nations, 2022). In China, it is estimated that by 2035, the population aged 60 and above will exceed 400 million, constituting more than 30% of the total population (Qian, 2022). Due to factors such as transitions in social roles and declines in physical functionality, older adults face heightened vulnerability to health risks compared to younger age groups (Smith et al., 2020). Consequently, the dissemination of health information has become a vital strategy for improving the health status of the elderly.

Nonetheless, challenges such as misinformation, digital fatigue, and the digital divide render older individuals more susceptible to health information avoidance behavior when confronted with an overwhelming amount of information. Health information avoidance is defined as the strategic behavior in which individuals actively ignore health-related content. Unlike the occasional avoidance seen in younger individuals, which may be triggered by temporary anxiety, health information avoidance in older adults is often rooted in a dual mechanism characterized by cognitive resource decline and a preference for emotional regulation. For instance, when faced with information about cancer screening guidelines or chronic disease management, older adults may maintain psychological equilibrium by consciously disregarding such information or physically distancing themselves from it (Niederdeppe et al., 2007). This seemingly irrational choice actually carries an adaptive function for coping with health information overload (Barbour et al., 2012).

In the short term, this avoidance mechanism may alleviate information anxiety associated with excessive health information exposure. However, in the long term, it can generate a vicious cycle characterized by declining health literacy and poor health decision-making (Niederdeppe et al., 2007). Therefore, this paper focuses on the factors influencing health information avoidance behavior among older adults. While numerous related studies exist, their conclusions are often limited by varying theoretical perspectives, resulting in fragmented insights. This study employs meta-analysis to quantitatively synthesize data across various studies, providing a comprehensive analysis of the factors influencing health information avoidance behavior among older adults. Additionally, using the Meta-Analytic Structural Equation Modeling method enables exploration of the underlying mechanisms in an integrated manner.

Literature Review

The Cognition–Affect–Conation (CAC) framework is a widely used process-oriented paradigm in cognitive psychology and behavioral science. It explains how individuals' subjective appraisals in response to external information are translated into emotional experiences and subsequently shape behavioral intentions and behavioral responses (Fishbein & Ajzen, 1975; Hilgard, 1980). The framework emphasizes that behavior is not a direct reaction to information exposure. Instead, it emerges through a sequential psychological process in which cognitive evaluations give rise to affective responses, which then inform behavioral tendencies. Within this framework, cognition refers to individuals' subjective judgments about information content and its potential consequences. Affect captures the emotional experiences that arise from these judgments, while conation represents the behavioral inclinations formed through the integration of cognitive and emotional processes. Because the CAC framework specifies this internal processing pathway, it has been widely applied in research on online health information behaviors, including health information seeking, use, and avoidance (Dai et al., 2020; Zhang & Gao, 2021).

In health communication and information behavior research, health information avoidance is commonly defined as a deliberate tendency to reduce, delay, or avoid exposure to health information that may be useful but is psychologically distressing (Howell & Shepperd, 2016; Sweeny et al., 2010). Existing studies indicate that health information avoidance is neither incidental nor irrational. Rather, it is closely embedded in individuals' subjective understandings of health risks and the emotional burden arising from those perceptions. Research on the mechanisms underlying health information avoidance has therefore focused primarily on the relationship between risk cognition and emotional responses, highlighting the central role of perceived health threats and their emotional consequences in shaping information-related behaviors (Sweeny et al., 2010).

Within this research tradition, subjective risk cognition is typically operationalized using variables derived from established risk appraisal approaches, including protection motivation research. These variables are used to capture individuals' early-stage risk judgments during information processing, particularly their assessments of the likelihood and potential severity of health threats. Such risk-related constructs have been widely employed in subsequent health information behavior studies to explain differences in emotional reactions and information engagement strategies, including avoidance (Floyd et al., 2000; Griffin et al., 1999). Building on this foundation, the present study adopts the CAC framework and incorporates perceived hazard characteristics and affective risk response as two well-established variables, corresponding to the cognitive and affective components of the model. These variables are used to capture key psychological processes underlying health information avoidance among older adults.

Perceived Hazard Characteristics (PHC) refer to individuals' subjective evaluations of specific health risks, focusing primarily on judgments about the likelihood of harm and the severity of its potential consequences. Perceived Susceptibility and Perceived Severity constitute the core dimensions of this construct and together reflect individuals' overall appraisal of health threats (Floyd et al., 2000; Griffin et al., 1999). When individuals perceive themselves to be at higher health risk, related health information is more likely to be interpreted as threatening, thereby providing a cognitive basis for subsequent emotional responses and information coping behaviors. It is important to note that perceived hazard characteristics and negative information characteristics, which will be discussed later, differ substantially in their theoretical level and object of influence. Specifically, perceived hazard characteristics refer to an individual's cognitive appraisal of the health risk or disease itself, that is, judgments about what the risk is and its potential consequences. For instance, in studies on cancer information behavior, Miles et al. (2008) found that older adults' avoidance of cancer information primarily stemmed from their perceptions of the severity and uncontrollability of the disease, along with the fear and fatalistic beliefs these perceptions engendered. This suggests that PHC emphasizes the individual's cognitive interpretation of the health threat itself. In contrast, negative information characteristics do not concern the health risk itself but rather the structural burdens associated with how information is communicated, such as information overload, poor information quality, or information fatigue. For example, during global public health crises, excessive and complex information can increase individuals' cognitive burden and induce anxiety, thereby prompting information avoidance (Soroya et al., 2021); false or conflicting information indirectly fosters avoidance by increasing uncertainty and cognitive effort (Vivion et al., 2024). Thus, NIC emphasizes how information is presented and its impact on an individual's information processing capacity. In summary, PHC and NIC explain the mechanisms underlying health information avoidance from two distinct dimensions: risk cognition and the information environment. The former emphasizes subjective appraisals of health threats, while the latter focuses on how information presentation occupies cognitive resources. Although theoretically distinct, both may jointly influence health information avoidance behavior through affective risk responses during information processing.

Affective Risk Response (AR) refers to the emotional experiences elicited when individuals confront health-related risks, most commonly manifested as fear, anxiety, and unease (Zhao et al., 2022). Cognitive appraisals of threat can activate self-protective motivation, which in turn shapes emotional responses (Balla & Hagger, 2025). When individuals perceive themselves to be exposed to higher levels of health risk, they tend to experience more intense affective reactions, including heightened anxiety and fear (Zhang et al., 2023). Moreover, population characteristics moderate this process. Individuals with higher perceived risk, particularly those with high perceived severity, exhibit stronger fear- and anxiety-related responses (Sand & Bristle, 2024). These affective risk responses may subsequently motivate individuals to avoid related health information. Especially when perceived coping resources are insufficient, avoidance and denial may function as maladaptive coping strategies, serving to alleviate the negative emotions triggered by threat perceptions. More concretely, when individuals possess sufficient cognitive resources, behavioral decisions are more likely to follow a rational-analytic pathway; however, when cognitive load exceeds manageable limits, affective heuristic processing tends to dominate. For older adults, age-related physiological decline not only constrains cognitive control capacity (Hess, 2015) but may also reduce the sustainability of health behaviors, thereby increasing reliance on affective heuristic pathways (Kim et al., 2011). In addition, older adults' perception of time is often characterized by a diminished sense of future self-continuity, which predisposes them to adopt cognitively simplifying strategies in decision-making as a means of reducing cognitive load (Bianconcini & Cagnone, 2021). Taken together, this body of research suggests a sequential transmission process linking cognitive appraisal and affective response. The following hypotheses are proposed:

H1: Perceived Hazard Characteristics is positively related to Affective Risk Response

(H1a) and Health Information Avoidance (H1b).

H2: Affective Risk Response is positively related to Health Information Avoidance.

In the era of the Internet and social media, information overload and misinformation have become another prominent explanatory pathway in research on health information avoidance. Negative Information Characteristics (NIC) refer to adverse features associated with information presentation and communicative capacity, including information overload, poor information quality, and information fatigue (Gong et al., 2024). When the complexity or volume of information exceeds individuals' available cognitive resources, individuals are more likely to adopt avoidance strategies (An & Wu, 2015). More specifically, information characterized by high emotional arousal intensifies cognitive load, thereby increasing the likelihood of avoidance behaviors (Soroya et al., 2021). For example, when individuals are exposed to volumes of information that surpass their cognitive processing capacity, namely information overload, they may experience cognitive burden, stress, and anxiety, which in turn directly or indirectly motivate disengagement from information (Shen et al., 2025). In addition, information quality problems, such as fake information or conflicting messages, increase cognitive effort and uncertainty, thereby indirectly encouraging information avoidance as a means of preventing psychological discomfort (Vivion et al., 2024). Information fatigue, defined as feelings of exhaustion or aversion resulting from prolonged or excessive exposure to repetitive or complex information, has also been shown to directly prompt individuals to proactively avoid further information engagement (Dai et al., 2020). The dynamics are particularly salient for older adults. Due to age-related declines in cognitive capacity and greater difficulty in using digital technologies, older adults may experience heightened anxiety, fear, and other negative emotional reactions when confronted with negative information characteristics such as information overload or misinformation. These affective reactions, in turn, increase their propensity toward health information avoidance

(Gu et al., 2025; Vivion et al., 2024). The following hypothesis is proposed:

H3: Negative Information Characteristics is positively related to Affective Risk Response (H3a) and Health Information Avoidance (H3b).

Finally, this study also examines the moderating effects of selected variables on the proposed process mechanisms. Regarding educational attainment, prior research among younger populations has reported a relatively stable moderating effect. However, studies focusing on older adults have produced opposite findings (Kirton & Dotson, 2016). The direction of moderation associated with cultural context is even more inconsistent across different research models. In some cases, collectivist cultures may reduce health information avoidance among older adults through sources of family support and shared responsibility (Lu et al., 2022). In other contexts, the externalization of health responsibility within collectivist settings may instead intensify avoidance tendencies among older adults (Ren, 2020). The present study proposes the following research question:

RQ: How do demographic variables (educational background, gender, age) and cultural background (Chinese culture vs. Western culture) moderate the influence paths of the above variables?

Taken together, this study develops a theoretical model of factors influencing health information avoidance among older adults, as illustrated in Figure 1.

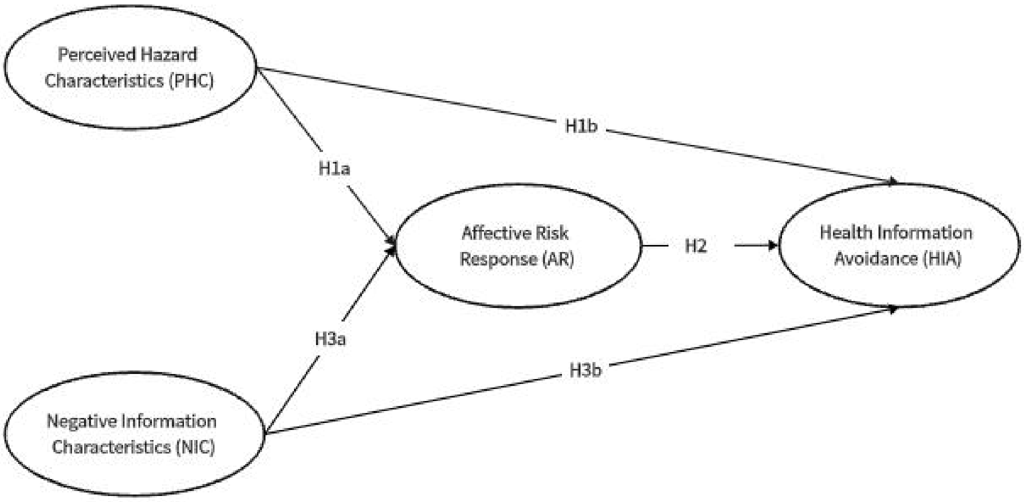


Figure 1. *Theoretical Model*

Method

This study primarily adopted Meta-Analytic Structural Equation Modeling (MASEM) for data analysis. Meta-analysis enables the quantitative integration of findings across studies and provides pooled parameter estimates. As an advanced methodological extension of meta-analysis, MASEM combines structural equation modeling with effect size matrices to allow for the simultaneous examination of multivariate relationships. The method follows a two-stage analytical framework. In the first stage, a two-stage meta-analytic structural equation approach is applied to construct a pooled covariance matrix through the weighted aggregation of correlation matrices. In the second stage, maximum likelihood estimation is used to assess model fit. Competing theoretical models are compared based on their fit indices to identify the model that demonstrates the most adequate fit (Cheung & Chan, 2005).

Study Selection

The study selection covered both English and Chinese publications. For English studies, data sources included PubMed, the Web of Science Core Collection, and Elsevier ScienceDirect, while Chinese-language searches were conducted using the China National Knowledge

Infrastructure (CNKI), the VIP Chinese Journal Database, and the Wanfang Data platform. To comprehensively capture the research landscape on health information avoidance among older adults, the search strategy employed a nested Boolean logic structure as follows: TS = ((health OR "chronic disease" OR cancer OR HIV OR diet OR nutrition OR vaccine) AND ("information avoidance" OR "information avoidance behavior") AND ("older adults" OR elderly OR geriatric OR senior))[1]. The search period spanned from database inception to December 2024, and no restrictions were imposed on publication type.

The initial search yielded 825 records, including 677 English-language studies and 148 Chinese-language studies. Using the built-in duplicate detection function of Zotero 6.0, 90 duplicate records were removed. A total of 735 studies then proceeded to the screening stage, comprising 619 English-language and 116 Chinese-language publications. The inclusion criteria were defined across the following dimensions and were independently applied by two researchers: (1) research content focused on factors influencing health information avoidance in older adults; studies not considering older adults and not using health information avoidance as the dependent variable were excluded. (2) studies without variable measurement and without quantitative assessment of the correlation between independent and dependent variables were excluded. (3) studies had to be full-text academic literature in Chinese or English; studies where full text could not be obtained were excluded. (4) research methods needed to be explicit with standardized data collection, processing, and analysis; studies not clearly reporting methods or with incomplete results were excluded. The literature identification and screening process is presented in Figure 2.

[1] The Chinese search strategy was designed to expand semantically related terms in Chinese and was specified as: 主题 = ((健康 + 慢性病 + 癌症 + 艾滋病 + 饮食 + 营养 + 疫苗) AND (信息回避 + 信息躲避 + 信息规避) AND (老年 + 老年人 + 银发 + 高龄)).

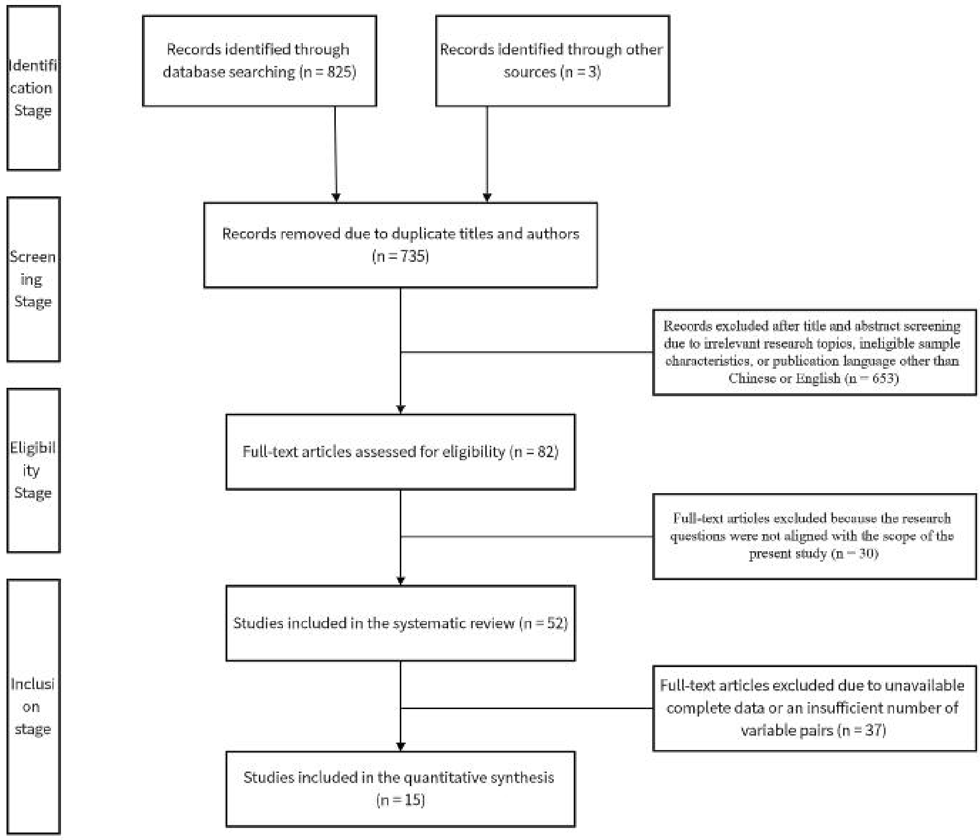


Figure 2. *PRISMA Flow Diagram for Study Selection*

During the title and abstract screening stage, 653 studies were excluded, primarily due to a lack of alignment between their research focus and the topic of the present study, or because their sample characteristics did not match the target population. The remaining 82 studies underwent a full-text review. From this group, 30 studies were excluded due to misalignment between their research questions and those of the current study, or because complete data were unavailable. As a result, 52 studies were preliminarily included, meeting the established quality criteria.

To further investigate the mechanisms by which various variables influence health information avoidance among older adults, a second-stage screening was conducted on the initially included studies. The inclusion criteria were as follows: (1) the study sample included older adults with a mean age of 55 years or above; (2) the research adopted an empirical quantitative design; studies based on theoretical frameworks, qualitative interviews, or mixed-method designs with inseparable qualitative data were excluded; (3) the study reported associations between health information avoidance and related variables, including correlation coefficients or statistics convertible into correlation coefficients, such as t-values, F-values, or regression coefficients; (4) the study satisfied the requirement for data independence. In cases where multiple publications from the same research team involved overlapping samples, only the version with the largest sample size and the most comprehensive reporting of variables was retained.

An additional 37 studies were excluded due to the absence of convertible effect sizes, as some reported only p-values or descriptive statistics, or because complete data could not be obtained. The final sample comprised 15 studies that met all quality criteria, including 8 publications in English and 7 in Chinese, yielding a cross-cultural dataset of 11,472 participants.

To enhance the comprehensiveness of the literature review, a backward snowballing strategy was implemented by examining the reference lists of the included studies, and no additional eligible studies were identified. The studies included in the meta-analysis are summarized in Table 1.

Table 1. *Literature Information Included in the Meta-Analytic Structural Equation Modeling*

Literature Info	Source	Publication Type	Sample Size
Gong Wen, 2024	Journal of International Communication	Core Journal	465
Wang Kunyu, 2023	Suzhou University	Dissertation	382
Zhang Ning, 2021	Library and Information	Core Journal	176
Pan Shuya, 2023	Journalism Evolution	Core/Extended Journal	211
Li Lin, 2021	Zhengzhou University	Dissertation	305
Zhang Qianhui, 2023	Xiangtan University	Dissertation	341
Peng Lihui, 2024	Information Science	Core Journal	281
Peiyi Lu, 2021	Journal of Aging and Health	Core Journal	4395
Anne Miles, 2008	Cancer Epidemiology, Biomarkers & Prevention	Core Journal	1442
Charlotte Vrinten, 2018	Psychology & Health	Core Journal	1568
Fuxiu Zhong, 2024	Frontiers in Psychology	Core Journal	236
Xusen Cheng, 2023	Information & Management	Core Journal	527
Xudong Gao, 2022	International Journal of Environmental Research and Public Health	Core Journal	907
Julia Nolte, 2022	The Journals of Gerontology: Series B	Core Journal	500
Chenyu Gu, 2024	JMIR Public Health and Surveillance	Core Journal	236

Effect Sizes and Literature Coding

Effect size serves as a standardized indicator of the strength of associations across studies, and its core function is to reduce the interference of measurement unit differences on the comparability of results. Following Cohen's classic definition (Cohen, 2016), the Pearson correlation coefficient *r* was adopted as the reference effect size metric. In the process of literature synthesis, three types of effect sizes were standardized. The first type consists of Cohen's *d* values reported in experimental designs, which were converted into *r* using the formulas proposed by Hedges and Olkin (2014). The second type includes standardized regression coefficients (β) reported in regression-based studies. These coefficients were transformed into r according to the empirical calibration equation developed by Peterson and Brown (2005), which helps mitigate the underestimation of coefficients caused by intercorrelations among predictors. The third type comprises standardized correlation coefficients *r* directly reported in the original studies. When the literature explicitly indicated that the data had been standardized, the reported *r* values were used without further transformation. All standardization procedures were implemented in the RStudio environment.

The purpose of literature coding is to transform characteristics of primary studies into structured indicators suitable for quantitative analysis through systematic data extraction. Drawing on the coding framework proposed by Lipsey and Wilson (2001) and guided by the theoretical model, a three-level coding scheme was developed. The descriptive level records study identifiers and sample characteristics, including authorship, year of publication, sample size, and mean participant age. The effect size level extracts correlation coefficient matrices among variables, with key variables including PHC, AR, NIC and HIA. The corresponding associations reflect hypothesized pathways such as NIC-PHC, PHC-AR and AR-HIA. The moderator level codes demographic characteristics, including dominant gender composition and categorized levels of educational attainment, as well as study context parameters such as measurement instrument reliability and the period of data collection.

Coding was conducted according to a standardized procedure. First, basic study information was recorded using structured Excel spreadsheets to ensure the traceability of authorship, publication year, and database source. Second, correlation coefficients among variables were extracted in line with the hypothesized pathways and converted into standardized effect sizes based on the effect size integration strategy. Demographic variables were coded following a dominant-group principle. Specifically, samples in which males accounted for 55% or more of participants were coded as 0 (male-dominant), whereas the remaining samples were coded as 1 (female-dominant). Educational attainment was dichotomized with reference to the International Standard Classification of Education

(ISCED), with junior secondary education or below coded as 0 and senior secondary education or above coded as 1. Cultural background was also coded dichotomously, with Chinese cultural background coded as 0 and Western cultural background coded as 1. Age was treated as a continuous variable, and reported mean ages were retained. For studies that reported only age ranges, median imputation was applied (Alwateer et al., 2024). Following Kirca et al. (2005), which suggests that at least three independent studies are required for meta-analytic estimation, the relationship specified in H3a could not be examined, whereas all other relationships met this criterion. The results of the literature coding are presented in Table 2.

Table 2. *Literature Coding for Included Meta-Analysis*

Basic Info	Correlation Relations	Sample Size	Correlation Coefficient	Education Background	Gender	Age	Cultural Background
Gong Wen, 2024	NIC-AR PHC-HIA AR-HIA	465	0.343 0.202 0.162	1	2	67	1
Wang Kunyu, 2023	AR-HIA	382	0.008	2	2	66	1
Zhang Ning, 2021	PHC-AR NIC-AR PHC-HIA AR-HIA	176	0.506 0.368 0.374 0.344		2	65	1
Pan Shuya, 2023	NIC-HIA	211	0.32	2	1	59	1
Li Lin, 2021	NIC-HIA	305	0.329	1	2	72	1
Zhang Qianhui, 2023	PHC-HIA	341	0.819	2	2	55	1
Peng Lihui, 2024	PHC-AR PHC-HIA AR-HIA	281	0.376 0.303 0.926	2	1		1
Peiyi Lu,2021	PHC-HIA	4395	0.271		2	64	2
Anne Miles,2008	PHC-HIA PHC-AR AR-HIA	1442	0.224 0.479 0.239		2	59	2
Charlotte Vrinten,201:	AR-HIA	1568	0.734	1	2	60	2
Fuxiu Zhong,2024	NIC-HIA	236	0.257	2	2	64	1
Xusen Cheng,2023	PHC-AR PHC-HIA AR-HIA	527	0.19 0.239 0.612	1	2		1
Xudong Gao,2022	NIC-HIA AR-HIA	907	0.253 0.217		2	71	1
Julia Nolte,2022	NIC-HIA PHC-HIA AR-HIA	500	-0.26 -0.31 -0.32		2		2
Chenyu Gu,2024	NIC-HIA	236	0.339		1	63	1

Note. PHC: Perceived Hazard Characteristics, AR: Affective Risk Response, NIC: Negative Information Characteristics, HIA: Health Information Avoidance.

Result

Heterogeneity Test

Random-effects model implemented using the Metafor package in R indicated substantial heterogeneity in the Pooled Effect Sizes across the four sets of variable relationships. Cochran's Q tests showed that the Q statistics for all hypothesized paths reached statistical significance (105.99-3068.66, $p < .001$), suggesting that the observed between-study variability exceeded what could be attributed to sampling error alone (Higgins et al., 2003).

The heterogeneity magnitude, as indexed by I^2, ranged from 94.20% to 99.70%, far surpassing the conventional threshold for high heterogeneity ($I^2 > 75\%$), and indicating systematic differences in true effect sizes across studies. Several theoretical explanations may account for this heterogeneity. First, the wide confidence interval observed for the perceived hazard characteristics-health information avoidance pathway (95% CI [-.08, .48]) may reflect construct-level differences in measurement instruments across studies. Second, variations in sample characteristics and cultural contexts may exert moderating effects. Accordingly, to adequately accommodate between-study variance components, parameter estimation was conducted using the DerSimonian-Laird random-effects model.

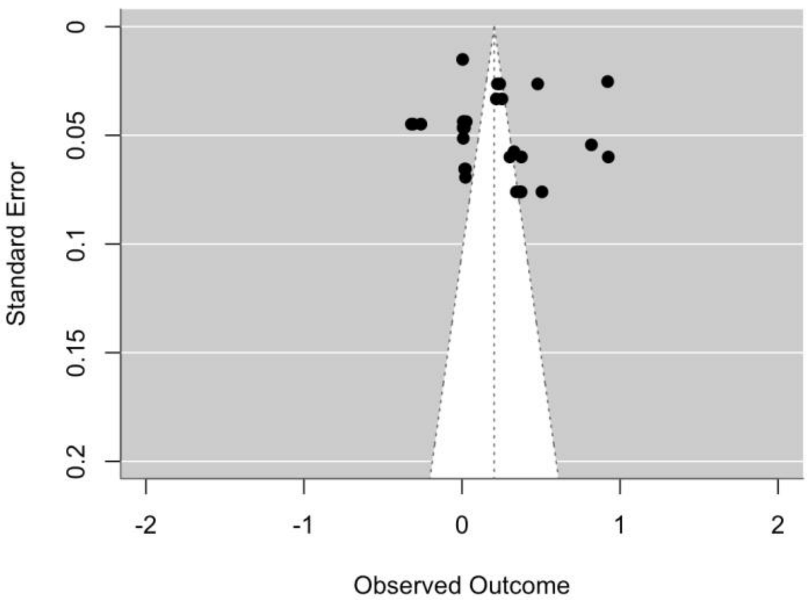
Publication Bias Test

Publication bias was assessed using a three-step diagnostic approach. First, funnel plots were visually inspected to examine the distribution of effect sizes against their standard errors. Second, Egger's regression tests were conducted as a quantitative assessment. Third, Rosenthal's fail-safe N was calculated to evaluate the potential impact of unpublished null findings. As shown in Figure 3, the funnel plots indicated that most studies were symmetrically distributed on both sides of the pooled mean effect size and concentrated toward the upper region of the plot, suggesting relatively small standard errors and a low likelihood of publication bias. This visual assessment was supported by the results of Egger's tests, as none of the regression intercepts for the hypothesized pathways reached statistical significance. To further quantify tolerance to potential publication bias, Rosenthal's fail-safe N was calculated. Taking the AR-HIA pathway as an example, a total of 132 unpublished studies with null effects ($N = 132$, $p < .001$) would be required to reduce the pooled effect size to a nonsignificant level, substantially exceeding Rosenthal's critical threshold (Rosenthal, 1979). Taken together, evidence from multiple diagnostic methods indicates that none of the examined pathways exhibited significant publication bias, suggesting a high level of robustness of the results.

Figure 3. *Funnel Plot*

Structural Equation Modeling Analysis

Within the two-stage MASEM framework, the flattened vectors of correlation coefficients



were first transformed into symmetric matrices using the vec2symMat function. To handle missing data, the three-stage hierarchical imputation approach was applied. Missing data were handled using a three-step hierarchical procedure. Studies with complete variable-level missingness were excluded via listwise deletion. For studies with partial missing data, cross-study weighted mean imputation was applied, with weights defined by the inverse of sample size. Extreme values were identified using Tukey's fences and replaced with the 95% Winsorized cutoff for the corresponding variable. Based on a random-effects specification, a pooled covariance matrix was constructed from the study-specific correlation matrices. The chi-square test (χ^2= 1979.07, df = 6, p < .001) indicated substantial heterogeneity in the original data, supporting the use of a random-effects model.

In line with the theoretical assumptions, PHC and NIC were specified as exogenous variables. AR was modeled as a mediating variable influenced by PHC, and HIA was specified as an endogenous variable influenced by PHC, NIC, and AR. Model fit indices indicated excellent fit to the data (RMSEA = .0028, SRMR = .0358, TLI = .9997, CFI = .9999). Information criteria further suggested a parsimonious and well-fitting model (AIC = -1.8182, BIC = -16.5136).

As shown in Figure 4, all hypothesized paths were statistically supported. The path coefficient from PHC to AR was .695 (S.E. = .051, $p < .001$), indicating a significant positive effect, supporting H1a. The direct effect of PHC on HIA was .794 (S.E. = .030, $p < .001$), supporting H1b. The path from AR to HIA was .215 (S.E. = .078, $p < .05$), indicating a significant positive effect and supporting H2. The path from NIC to HIA was .600 (S.E. = .023, $p < .001$), supporting H3b. In terms of standardized coefficients, the strongest effect was observed for the PHC-HIA path ($\beta = .794$), followed by PHC-AR ($\beta = .695$) and NIC-HIA ($\beta = .600$), whereas the AR-HIA path showed a comparatively weaker effect ($\beta = .215$).

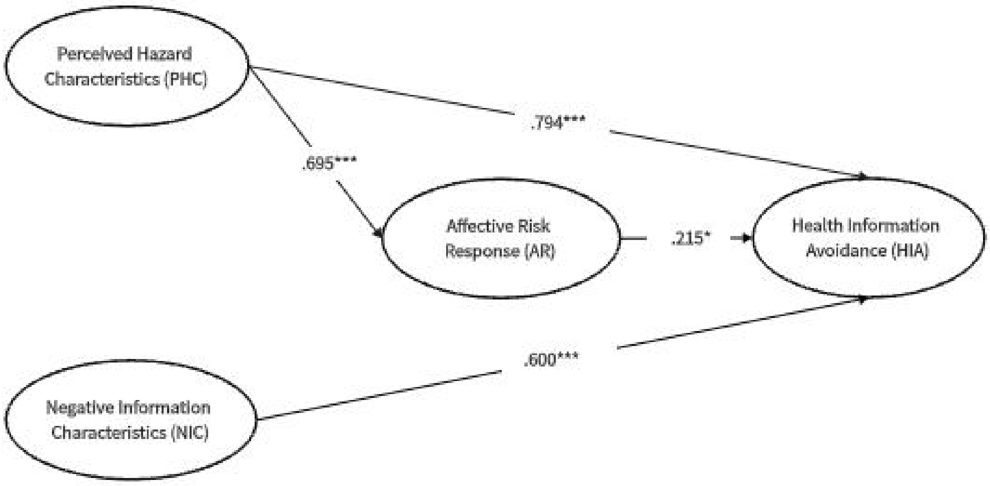


Figure 4. *Path Coefficients*

Moderating Effect Test

The included studies exhibited substantial heterogeneity, suggesting the presence of potential moderating variables. To address the research question, random-effects models were therefore employed to examine the moderating roles of gender, age, educational attainment, and cultural background.

The moderating effect of gender revealed a divergent pattern. Among older women, perceived hazard characteristics were significantly associated with affective risk responses (male: $r = .38$, 95% CI [-.18, .93] vs. female: $r = .33$, 95% CI [.01, .65]). In contrast, among older men, affective risk responses showed a stronger association with health information avoidance (male: $r = .93$, 95% CI [.21, 1.64] vs. female: $r = .18$, 95% CI [-.07, .43]). These findings indicate that older women are more likely to experience emotional responses in reaction to perceived hazards, whereas health information avoidance among older men appears to be more strongly driven by affective responses.

Age significantly moderated the NIC-HIA pathway ($\beta = .02$, $p < .01$). Similarly, the effect of PHC on HIA increased with age ($\beta = .05$, $p < .05$). Together, these results suggest that as age increases, older adults' capacity or willingness to process health information may decline, accompanied by a stronger tendency toward information avoidance.

Moderation analysis by educational attainment showed that the effect of NIC on HIA was significantly stronger among individuals with a high school education or above ($r = .27$, 95% CI [.22, .33]) than among those with a middle school education or below ($r = .02$, 95% CI [-.07, .11]). This pattern suggests that individuals with lower educational attainment may be less able to interpret complex information, which in turn is associated with higher levels of information avoidance.

When cultural background was examined as a moderator, the PHC-HIA pathway was significant and positive in the samples with Chinese cultural background ($r = .58$, $p < .05$, 95% CI [.01, .69]) but not significant in the samples with Western cultural background (r = -

.029, $p > .05$, 95% CI [-.48, .42]). This indicates that older adults with Chinese cultural background are more likely to engage in health information avoidance in response to perceived hazards.

A similar cultural pattern emerged for the NIC-HIA pathway. In Chinese culture, NIC was positively associated with HIA ($r = .37$, $p < .05$, 95% CI [.00, .39]), whereas in Western culture the association was negative but only marginally significant ($r = -.26$, $p < .10$, 95% CI [-.51, .02]). These findings suggest that negative information characteristics are more likely to elicit information avoidance among older adults with Chinese cultural background.

No significant moderating effects were observed for the PHC-AR pathway or the AR-HIA pathway.

Discussion and Conclusion

This study employed MASEM to examine the effects of Perceived Hazard Characteristics, Affective Risk Response, and Negative Information Characteristics on health information avoidance among older adults, and to investigate the moderating roles of gender, age, educational background, and cultural background. The main findings indicate that both PHC and NIC are positively associated with HIA, and that AR may function as a mediating mechanism between PHC and HIA. Lower education level, higher age, and Chinese cultural background strengthen the effects of different information characteristics on information avoidance, whereas gender exhibits a more complex pattern of associations.

As individuals' subjective cognition of specific health risks, PHC has long been regarded as a key driver of health-related behaviors. However, our findings suggest that older adults may rely on a distinct coping mechanism when encountering health information. PHC exerts not only a significant direct effect on health information avoidance but also a significant indirect effect through AR. When individuals perceive a high level of health threat and lack sufficient coping resources, emotional reactions are likely to activate defensive motivation, which in turn leads to avoidance behavior. Prior research has shown that older adults tend to rely more on heuristic processing rather than systematic processing when handling information (Carstensen et al., 1999). As a result, their responses to highly threatening information are more likely to take the form of rapid, experience-based emotional reactions rather than deliberate cost–benefit evaluations. For example, cancer risk information, due to its high level of perceived threat, is more likely to evoke associations with uncontrollability, thereby eliciting negative emotions and avoidance behaviors as a means of maintaining psychological stability (Miles et al., 2008).

Similarly, NIC shows a significant direct effect on health information avoidance among older adults. This finding indicates that negative content is not only a trigger for passive information avoidance but may also serve as an antecedent of active avoidance strategies in this population. People have limited attentional resources when processing complex information, and trade-offs inevitably occur in the allocation of attention (Yang, 2024). This constraint is more pronounced among older adults. With increasing age, cognitive aging processes such as reduced processing speed and declining working memory capacity directly limit sustained engagement with complex information. When negative health information is combined with high emotional arousal, high technical complexity, and redundant informational structures, individuals are more likely to experience cognitive fatigue or information aversion, which in turn promotes information avoidance. The technological structure of media underlying contemporary health communication further intensify this problem. On social media platforms, for example, algorithms designed to increase user stickiness frequently push highly emotional and high-click negative content. After prolonged and dense exposure to such information, older users not only experience emotional pressure but also become fatigued and desensitized due to the repetitive nature and low practical utility of the content (Liu & Zeng, 2021).

It is noteworthy that the present study was unable to test the hypothesized path from NIC to risk-related affective responses, primarily because only two existing empirical studies reported data measuring both constructs simultaneously (Zhang & Gao, 2021), which falls short of the minimum number of studies required for meta-analytic integration (Kirca et al., 2005). This gap is not incidental, rather, it reflects a notable neglect in the literature regarding the independent influence of information features on older adults' emotional responses, which has received far less attention compared with research on affective responses to perceived hazard characteristics, such as disease severity. This research bias can be traced first to the dominance of classical frameworks in health information behavior research, including Protection Motivation Theory and the Extended Parallel Process Model. These theories emphasize a sequential process involving risk appraisal, threat appraisal, affective response, and behavioral coping (Rogers, 1975; Witte, 1992), in which AR is conceptualized primarily as a reaction to PHC, rather than as a direct response to information presentation. Within this framework, information is treated largely as a vehicle for risk cognition, and its structural features such as overload, misinformation, or fatigue-inducing properties are not ascribed independent affective influence. Consequently, researchers have primarily focused on perceived severity or susceptibility as drivers of AR, while largely neglecting the direct affective effects of NIC. For example, Miles et al. (2008) emphasized disease-related fear and fatalism in older adults' cancer information avoidance, without considering the emotional consequences of information presentation.

Second, the real-world context of health research among older adults further exacerbates this issue. The inherent severity of diseases such as cancer or chronic illnesses exerts a strong emotional impact, often overshadowing the affective influence of information features. Researchers and practitioners commonly assume, intuitively, that older adults' fear or anxiety in response to health information primarily derives from concern about disease outcomes rather than from how information is presented. For instance, Cheng et al. (2023) found that in examining the effect of technological stress on older adults' information avoidance, the emotional impact of perceived disease risk was substantially greater than that of information presentation. Similarly, Lu et al. (2021) reported that older adults' fear of COVID-19 infection outcomes was the main emotional driver of information avoidance, while the emotional effect of information overload was not separately highlighted. Such findings reinforce scholarly focus on affective responses to disease severity, further marginalizing the investigation of the independent emotional impact of information characteristics.

Third, existing research on older adults' health information avoidance has often adopted a cognitive-behavioral paradigm, emphasizing rational-analytic pathways through which NIC influences HIA via cognitive load or processing difficulty, treating AR as a byproduct rather than an independent mediating mechanism. For example, in their study on older adults' avoidance of health information on WeChat, Pan et al. (2023) focused solely on the direct effects of information quality and information overload. Although they briefly noted the potential mediating role of emotions in their discussion section, this mechanism was not formally integrated into their empirical analytical framework.

The analysis of moderating effects provides additional evidence for group differences in health information avoidance among older adults. Older individuals and those with lower levels of education are more likely to avoid health information characterized by threat, repetition, or falsehood. This pattern may reflect weaker information processing capacity and strategic regulation ability, which make it more difficult to maintain rational evaluation and emotional regulation under conditions of high emotional load. Gender differences show a clearer differentiation. Older women are more likely to generate emotional responses to threatening information, which may result from a combination of biological differences and gender roles. However, emotional responses do not necessarily translate into avoidance. Among older men, emotional responses appear more likely to reinforce avoidance tendencies.

The moderating effect of cultural background reveals sociocultural differences in HIA. Among older adults with Chinese cultural background, both PHC and NIC are associated with stronger information avoidance. This pattern may be related to cultural norms rooted in Confucian traditions, such as the emphasis on maintaining harmony, face, and fatalistic orientations toward health. In collectivist cultures, negative emotions are often regarded as threats to group harmony (Hofstede, 2011), while severe illnesses are deeply intertwined with both individual and family face (Yang & Kleinman, 2008). Furthermore, the prevalence of fatalistic health beliefs in East Asian societies may weaken older adults' perceived sense of agency and influence their coping strategies toward threatening health information (Heiniger et al., 2015). Compounding these factors, lower levels of eHealth literacy among East Asian older adults may further elevate the cognitive burden associated with information fatigue and information evaluation (Yoon et al., 2020). These findings suggest that future health communication design should place greater emphasis on audience segmentation and strategy matching, shifting from the assumption that content is universally important to a focus on whether information is appropriate for specific groups.

Several limitations should be acknowledged. First, literature search was limited to studies published in Chinese and English, potentially excluding relevant research in Korean and other languages, which may weaken the generalizability of the findings, particularly with respect to cultural background. Second, due to the minimum study requirements for meta-analysis, the key pathway from NIC to AR, as well as variables such as subjective norms and information credibility, were not included. Future research should expand multilingual databases, accumulate additional empirical evidence, and integrate qualitative approaches and more complex models in order to strengthen theoretical explanations and practical applicability.

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