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Social Media and Health Information Among Middle-Aged and Elderly People: Exploring Knowledge Gaps and Rumor Spread Mechanisms in Changsha, China

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Abstract

Background*: The digital revolution has transformed health information dissemination among middle-aged and elderly populations in China. With over 140 million internet users aged 60 and above, social media platforms have become primary health information channels. However, this demographic faces significant challenges including digital divide constraints and high susceptibility to health-related rumors, which account for 42% of all rumors targeting older adults.*

Objective*: This study investigates mechanisms underlying health information dissemination behaviors among middle-aged and elderly social media users, examining how health information literacy, social support networks, and cognitive processing ability influence information acquisition capabilities and rumor dissemination propensity.*

Methods*: A mixed-methods design surveyed 472 active social media users aged 50-75 in Changsha using structural equation modeling to test eight hypotheses across five constructs: health information literacy, social support networks, cognitive processing ability, health information acquisition ability, and rumor dissemination propensity. Qualitative analysis conducted in-depth interviews with 15 participants, analyzed through NVivo14 thematic coding.*

Results*: All hypotheses received empirical support with exceptional explanatory power (R^2 = 92.3%, 81.5%, 73.3% for key constructs). Health information literacy demonstrated extraordinarily strong influence on cognitive processing ability (β = 0.856, f^2 = 2.747), establishing itself as the foundational element of health communication ecology. Cognitive processing and information acquisition abilities both significantly suppressed rumor dissemination (β = -0.589, β = -0.572). Social support networks indirectly influenced rumor propensity through information acquisition mediation (β = 0.221). Qualitative analysis revealed "authority orientation plus experiential verification" evaluation patterns and socially-driven dissemination behaviors shaped by socioeconomic stratification.*

Conclusion*: Health information dissemination among older adults constitutes a complex adaptive system involving individual cognitive schemas, social networks, economic constraints, and institutional supports. The research provides theoretical foundations for understanding digital health communication and practical guidance for designing targeted interventions to enhance information literacy and reduce rumor propagation in aging societies.*

Keywords*: Health Information Dissemination,Social Media,Middle-aged and Elderly People,Gaps in Health Knowledge,Rumor Propagation*

1. INTRODUCTION

The Digital Wave in the Post-Pandemic Era: Reshaping Health Information Dissemination in Chinese Society. The digital wave in the post-pandemic era is profoundly reshaping the landscape of health information dissemination in Chinese society. By 2023, the number of internet users in China had reached 1.092 billion, with individuals aged 60 and above accounting for 13.0%—approximately 140 million people (CNNIC, 2024). This vast group of middle-aged and elderly internet users exhibits distinct patterns of health information dissemination on social media platforms. During the COVID-19 pandemic, the widespread adoption of digital tools such as the "health code" forced middle-aged and elderly individuals to accelerate their integration into digital life. However, this passive digital transformation has also exposed severe generational digital divide issues (Chongcharoen et al., n.d.).

Mainstream social media platforms such as WeChat and Douyin have become crucial channels for middle-aged and elderly people to access health information. Research data indicate that over 75% of middle-aged and elderly internet users receive health-related information through social media daily, yet only 30% can accurately assess its reliability (Liu et al., 2023). This deficiency in information discernment contrasts sharply with their strong demand for health information, creating fertile ground for the spread of health-related rumors. According to the 2023 National Internet Rumor-Refuting Platform, health-related rumors targeting middle-aged and elderly people accounted for as much as 42%, displaying a pronounced social network clustering effect (Du et al., 2023).

Recent studies in health communication reveal a deep-seated contradiction between social media's algorithmic recommendation mechanisms and the cognitive characteristics of middle-aged and elderly individuals. Algorithms tend to push emotionally charged and overly simplistic health content, while middle-aged and elderly people often lack the necessary media literacy to evaluate the scientific validity of such information. A longitudinal study by Zhang & Wang (2024) found that health information dissemination among middle-aged and elderly people on social media exhibits a "strong ties, weak recognition" pattern: they are more likely to trust and share health information from acquaintances, yet their ability to assess the authenticity of the information itself remains weak (Li & Khan, n.d.).

At the same time, there is significant internal stratification in the health knowledge acquisition capabilities of the middle-aged and elderly population. Differences in education level, economic status, and digital literacy place some individuals at a disadvantage in accessing health information. This "secondary digital divide" not only affects individual health decision-making but may also amplify health knowledge inequality through cascading effects in social networks (Quan & Khan, 2024). Recent empirical studies suggest that middle-aged and elderly individuals with higher socioeconomic status tend to have access to higher-quality health information and possess stronger information evaluation skills, whereas those on the social periphery are more susceptible to false health information (Chen et al., 2024).

This complex reality underscores the urgency of studying the health information dissemination behaviors of middle-aged and elderly individuals on social media. A deeper understanding of the knowledge acquisition gap and the mechanisms of rumor propagation is not only of significant theoretical value but also provides empirical support for designing targeted health communication interventions (Zhang & Khan, 2024).

2. RESEARCH DESIGN

This study adopted a mixed-methods research design employing an explanatory sequential approach to investigate health information dissemination mechanisms among middle-aged and elderly social media users. The design integrated quantitative and qualitative methods to provide comprehensive insights into the complex phenomenon of health information sharing and rumor propagation.

2.1 Quantitative Research Design

The quantitative component utilized a cross-sectional survey design with structural equation modeling (SEM) to examine causal relationships among key variables. Five latent constructs were operationalized: Health Information Literacy (traditional literacy, health literacy, media literacy), Social Support Network (network size, relationship strength, information accessibility), Cognitive Processing Ability (information comprehension, critical thinking, decision-making), Health Information Acquisition Ability (search, filtering, application capabilities), and Rumor Dissemination Propensity (forwarding behavior, verification practices, dissemination motivation). Multi-stage stratified sampling was employed to recruit 472 participants from active social media users aged 50-75 in Changsha who spend more than 10 hours weekly on social platforms. Sample size was calculated using finite population formula with 95% confidence level and ±4.5% sampling error, exceeding SEM requirements of 20 times the observed variables.

Data collection utilized online surveys with validated measurement scales adapted from established instruments, employing 5-point Likert scales. Statistical analysis included descriptive statistics, reliability and validity testing, correlation analysis, and SEM using SmartPLS4 software to test hypothesized relationships and model fit.

2.2 Qualitative Research Design

The qualitative component employed a phenomenological approach using semi-structured in-depth interviews to explore participants' lived experiences with health information dissemination. Maximum variation sampling was used to select 15 key informants representing diverse backgrounds across three stratification criteria: socioeconomic status (high, middle, low income/education levels), health information dissemination activity (low: 0-1 times daily, medium: 2-5 times, high: >5 times), and rumor identification ability based on prior survey results. Face-to-face interviews lasting 60-90 minutes were conducted using a structured interview guide focusing on information acquisition channels, evaluation criteria, dissemination motivations, and rumor identification experiences. All sessions were audio-recorded and transcribed verbatim. Grounded theory methodology guided the qualitative analysis using NVivo14 software. Data were coded through open, axial, and selective coding processes to identify emerging themes and patterns. Thematic analysis revealed key concepts including "strong trust, weak verification" dynamics in health information sharing behavior.

3. Positive research

We employed Partial Least Squares (PLS) modeling and used SmartPLS 4 as a statistical tool to examine the measurement and structural models.

3.1 Reliability and Validity Analysis

The measurement model evaluation was conducted following Hair et al. (2022) guidelines using SmartPLS 4.0 software. The study employed five latent constructs: Health Information Literacy, Social Support Network, Cognitive Processing Ability, Health Information Acquisition Ability, and Rumor Dissemination Propensity, each measured through multiple observed indicators

using 5-point Likert scales.

Table 1 Measurement Model

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Cognitive Processing Ability	0.973	0.973	0.976	0.821
Health Information Acquisition Ability	0.972	0.972	0.975	0.816
Health Information Literacy	0.961	0.962	0.967	0.764
Rumor Dissemination Propensity	0.968	0.968	0.972	0.796
Social Support Network	0.962	0.963	0.968	0.768

3.1.1 Internal Consistency and Reliability

All constructs demonstrated excellent internal consistency, with Cronbach's alpha values exceeding 0.96, significantly surpassing the 0.7 threshold. Composite reliability measures (rho_A and rho_C) also exceeded 0.96 for all variables, confirming strong correlations among items measuring each construct. These results indicate that the measurement instruments consistently measure their intended latent constructs.

3.1.2 Convergent Validity

Average Variance Extracted (AVE) values ranged from 0.764 to 0.821, well above the 0.5 threshold, confirming good convergent validity. Cognitive Processing Ability showed the highest AVE (0.821), indicating greatest consistency among its measurement indicators, while Health Information Literacy had the lowest but still acceptable AVE (0.764).

3.1.3 Discriminant Validity

Table 2 Discriminant Validity (HTMT)

	Cognitive Processing Ability	Health Information Acquisition Ability	Health Information Literacy	Rumor Dissemination Propensity	Social Support Network	Health Information Literacy x Cognitive Processing Ability
Cognitive Processing Ability						
Health Information Acquisition Ability	0.765					
Health Information Literacy	0.850	0.817				
Rumor Dissemination Propensity	0.705	0.823	0.797			
Social Support Network	0.848	0.835	0.807	0.768		

Health Information Literacy x Cognitive Processing Ability	0.160	0.172	0.074	0.203	0.057	

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT) method. Most HTMT values between construct pairs were below 0.85, indicating good discriminant validity. The relationship between Health Information Literacy and Cognitive Processing Ability showed the highest HTMT value (0.850), sitting at the threshold boundary but still indicating statistical distinguishability. Bootstrap confidence interval analysis (5,000 subsamples) confirmed that all HTMT confidence intervals excluded 1, further validating discriminant validity.

3.2 Structural Model

3.2.1 Collinearity Assessment

Variance Inflation Factor (VIF) analysis revealed no serious collinearity issues, with all values ranging from 3.267 to 4.931, below the critical threshold of 5. Information Filtering Ability showed the highest VIF (4.931), followed by Media Literacy (4.924), but both remained within acceptable limits.

3.2.2 Path Relationships and Effect Sizes

The structural model revealed significant relationships among all constructs. Health Information Literacy demonstrated the strongest effect on Cognitive Processing Ability ($\beta = 0.856$, $t = 33.288$, $f2 = 2.747$), indicating an extremely large effect size. Health Information Acquisition Ability showed a strong negative effect on Rumor Dissemination Propensity ($\beta = -0.572$, $t = 6.631$, $f2 = 0.169$), representing a medium to large effect.

Cognitive Processing Ability significantly influenced both Health Information Acquisition Ability ($\beta = 0.463$, $t = 10.200$, $f2 = 0.442$) and Rumor Dissemination Propensity ($\beta = -0.324$, $t = 3.402$, $f2 = 0.166$). Social Support Network showed a moderate positive effect on Health Information Acquisition Ability ($\beta = 0.386$, $t = 7.836$, $f2 = 0.250$).

3.2.3 Mediation Analysis

Indirect effects analysis revealed complex mediation pathways. Health Information Literacy's indirect effect on Rumor Dissemination Propensity ($\beta = 0.588$, $t = 9.129$) was substantially larger than any direct effect, indicating that literacy primarily suppresses rumor dissemination through mediation chains involving cognitive processing and information acquisition abilities. The indirect effect of Health Information Literacy on Health Information Acquisition Ability ($\beta = 0.396$, $t = 9.619$) exceeded its direct effect ($\beta = 0.145$) by approximately 2.7:1, suggesting that literacy mainly enhances acquisition ability by improving cognitive processing.

3.2.4 Model Explanatory Power

The model demonstrated strong explanatory power with R2 values of 0.923 for Health Information Acquisition Ability, 0.815 for Rumor Dissemination Propensity, and 0.733 for Cognitive Processing Ability. These high R2 values indicate that the theoretical framework effectively explains variance in health information behaviors among middle-aged and elderly populations.

3.3 PLS-Predict

Cross-validation using blindfolding procedures confirmed strong predictive relevance. Q2predict values were positive for all constructs: Health Information Acquisition Ability (0.864), Cognitive Processing Ability (0.731), and Rumor Dissemination Propensity (0.685), all indicating strong

predictive power.

Individual indicator Q2predict values ranged from 0.530 to 0.721, with Information Search Ability (0.721) and Information Filtering Ability (0.715) showing the highest predictive relevance. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values were consistently lower for the PLS-SEM model compared to linear models, confirming superior predictive accuracy.

Table 3PLS-Predict

	Q2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
CT	0.563	0.645	0.428	0.652	0.437
DA	0.631	0.583	0.406	0.590	0.419
IC	0.650	0.536	0.344	0.545	0.412
IA	0.681	0.587	0.401	0.592	0.414
IF	0.715	0.495	0.392	0.581	0.396
IS	0.721	0.510	0.394	0.590	0.407
DM	0.530	0.703	0.400	0.723	0.502
IB	0.576	0.694	0.476	0.697	0.504
IV	0.585	0.709	0.493	0.717	0.504

Note: CT= Critical Thinking;DA = Decision-Making Ability;IC= Information Comprehension Ability;IA = Information Application Ability;IF = Information Filtering Ability;IS = Information Search Ability; DM = Dissemination Motivation; IB= Information forwarding behavior; IV= Information Verification Behavior.

4. **RESULTS**

4.1 SmartPLS4 Results

As recommended by Hair et al. (2017) and Cain et al. (2017), we evaluated multivariate skewness and kurtosis. The results indicate that the collected data is not multivariately normal, with Mardia's multivariate skewness (β=5.115, p=0.000**) and Mardia's multivariate kurtosis (β=62.566, p=0.000**). Therefore, following the suggestion of Hair et al. (2019), we reported path coefficients, standard errors, t-values, and p-values for the structural model using bootstrapping with 5000 resampled samples.

4.1.1 Hypothesis Testing - Direct Effects

Table 4 Hypothesis Testing Direct Effects

Hypothesis	Relationship	Std Beta	t-values	p-values	BCI LL	BCI UL	f2	VIF
H1	Health Information Literacy -> Health Information Acquisition Ability	0.541	10.452	0.000*	0.441	0.647	0.655	4.647
H2	Social Support Network -> Health Information Acquisition Ability	0.386	7.836	0.000*	0.284	0.481	0.250	2.178
H3	Cognitive Processing Ability -> Health Information Acquisition Ability	0.463	10.200	0.000*	0.374	0.552	0.429	3.929
H4	Health Information Acquisition Ability -> Rumor Dissemination Propensity	-0.572	6.631	0.000*	-0.400	-0.740	0.169	4.102

H7	Cognitive Processing Ability -> Rumor Dissemination Propensity	-0.589	7.809	0.000*	-0.446	-0.744	-0.566	-3.654
H8	Health Information Literacy -> Cognitive Processing Ability	0.856	33.288	0.000*	0.800	0.901	2.747	1.000

All eight hypotheses received empirical support through bootstrap analysis (5,000 samples, 95% CI). The strongest relationship was between Health Information Literacy and Cognitive Processing Ability (H8: $\beta = 0.856$, $t = 33.288$, $p < 0.001$, $f2 = 2.747$), indicating an extremely large effect size that positions health information literacy as a primary determinant of cognitive processing patterns.

Health Information Literacy positively influenced Health Information Acquisition Ability (H1: $\beta = 0.541$, $t = 10.452$, $p < 0.001$, $f2 = 0.655$), representing a large effect. However, decomposition analysis revealed that this total effect comprised a small direct effect ($\beta = 0.145$) and a substantial indirect effect ($\beta = 0.396$) mediated through cognitive processing ability.

Social Support Network demonstrated a significant positive effect on Health Information Acquisition Ability (H2: $\beta = 0.386$, $t = 7.836$, $p < 0.001$, $f2 = 0.250$), reflecting a medium to large effect that validates social capital theory in digital health information contexts.

Cognitive Processing Ability showed significant positive influence on Health Information Acquisition Ability (H3: $\beta = 0.463$, $t = 10.200$, $p < 0.001$, $f2 = 0.442$) and negative effects on Rumor Dissemination Propensity (H7: $\beta = -0.589$, $t = 7.809$, $p < 0.001$, $f2 = 0.566$), highlighting its dual role in enhancing information capabilities while suppressing rumor behaviors.

Health Information Acquisition Ability significantly reduced Rumor Dissemination Propensity (H4: $\beta = -0.572$, $t = 6.631$, $p < 0.001$, $f2 = 0.169$), confirming that enhanced information skills directly counter rumor spreading behaviors.

4.1.2 Mediation and Moderation Effects

Table 5 Hypothesis Testing Mediation and Moderation Effects

Hypothesis	Relationship	Std Beta	t-values	p-values	BCI LL	BCI UL
H5	Social Support Network -> Health Information Acquisition Ability -> Rumor Dissemination Propensity	0.221	0.000*	0.144	0.300	0.221
H6	Health Information Literacy x Cognitive Processing Ability -> Rumor Dissemination Propensity	-0.031	0.001	0.949	-0.012	-0.031

Note: We use 95% confidence interval with a bootstrapping of 5,000

The mediation hypothesis (H5) was supported, showing that Social Support Network influences Rumor Dissemination Propensity through Health Information Acquisition Ability ($\beta = 0.221$, $t = 5.529$, $p < 0.001$). This full mediation indicates that social networks primarily reduce rumor propensity by enhancing individual information acquisition capabilities rather than through direct mechanisms.

The moderation hypothesis (H6) revealed a significant interaction effect between Health Information Literacy and Cognitive Processing Ability on Rumor Dissemination Propensity (β = -0.031, t = 3.279, p = 0.001). Although small in magnitude, this negative moderation suggests synergistic effects where higher health information literacy amplifies the rumor-suppressing impact of cognitive processing ability.

4.2 Nvivo Results

Thematic Analysis Framework

Qualitative analysis of 15 in-depth interviews using NVivo 14 revealed five major themes that contextualize and extend quantitative findings: (1) Diverse Health Information Acquisition Behaviors, (2) Cognitive Mechanisms in Information Evaluation, (3) Social Drivers of Information Dissemination, (4) Socioeconomic Stratification Effects, and (5) Occupational Background Influences.

4.2.1 Theme 1: Health Information Acquisition Behavior Patterns

Word frequency analysis revealed "community," "doctor," and "WeChat groups" as dominant keywords, reflecting integration of traditional medical authorities with emerging social media platforms. Community health programs formed crucial information foundations through activities like "free blood pressure measurement twice monthly" and neighbor-driven participation models creating unique health information ecosystems.

WeChat groups functioned as digital information hubs with hierarchical network structures comprising "health discussion groups," "family groups," and "peer dance groups." Users exhibited distinct temporal browsing patterns with "twice daily checking" and "20-40 minute sessions," necessitating health content that could be "readable within seconds."

Technical difficulties created significant acquisition barriers, with frequent errors in "screen swiping" and "link clicking" demonstrating concrete digital divide manifestations. Community-based "smartphone training classes" and "elderly health education" emerged as key mechanisms bridging digital literacy gaps.

4.2.2 Theme 2: Information Evaluation Cognitive Mechanisms

Information evaluation exhibited clear "authority orientation plus experiential verification" characteristics. Professional endorsement remained the primary credibility criterion, with respondents seeking markers like "doctor speaking" or "written by hospital nutrition department." This heuristic strategy proved efficient but vulnerable to disguised authoritative information.

Cross-verification strategies showed clear educational stratification. Higher-educated respondents could cross-check using official channels like "provincial hospital public accounts," while lower-educated groups relied more on social verification through "friends' experiences." Professional terminology complexity created major evaluation bottlenecks, with medical terms causing cognitive overload and triggering either family assistance-seeking or comprehension avoidance.

Emotional resonance played unique evaluation roles through "gentle language," "friendly tone," and "real-life cases" enhancing information acceptability. Regional identity statements like "also from Hunan" effectively reduced psychological distance and facilitated comprehension.

4.2.3 Theme 3: Social Dissemination Behavior Drivers

Forwarding decisions reflected unique social rationality transcending mere information transmission, embodying complex motivations including group cohesion and care expressions. Content value judgments showed pragmatic orientation with "simple, feasible, low-threshold" concerns becoming key forwarding determinants.

Risk considerations and social face concerns constituted important forwarding constraints. Emotional responses like "fear of misleading others" and "group member doubts" reflected profound social reputation impacts on dissemination behaviors. Mistaken forwarding shame created sustained behavioral inhibition, generating self-correcting feedback mechanisms.

Social network interactions exhibited "positive cycles plus correction mechanisms" duality. Group discussions around "sharing personal experiences" illustrated experiential knowledge social construction, enhancing cohesion while providing misinformation spread opportunities. Correction mechanism effectiveness faced constraints from social face concerns, with many choosing "silent corrections" over open error acknowledgment.

4.2.4 Theme 4: Socioeconomic Stratification Structural Impacts

Economic constraints fundamentally influenced health information consumption decisions. Pension levels directly restricted health product purchasing decisions, with statements like "can't afford thousand-yuan treadmill" illustrating resource scarcity choice constraints. Economic rationality extended to information channel choices, automatically excluding premium resources due to price barriers.

Medical insurance coverage and government subsidy policies constituted important information filtering mechanisms. Information about "reimbursement scope" and "government dental subsidies" received priority attention and rapid dissemination. Institutional trust significantly enhanced information credibility through joint government-medical endorsements.

Educational stratification proved particularly evident in digital health literacy. Highly educated groups demonstrated superior "professional terminology understanding" and "multi-source comparison" capabilities, while lower-educated groups preferred "illustrated texts" and "short videos with icons." This literacy gap determined both comprehension depth and dissemination capacity across different groups.

4.2.5 Theme 5: Occupational Background Cognitive Schema Continuity

Professional background analysis revealed "responsibility," "health," "medical," and "professional" as high-frequency keywords, indicating occupational background's important role in health information behaviors. Medical staff, teachers, and grassroots cadres demonstrated stronger "social responsibility" perception and proactive knowledge updating.

Professional knowledge provided superior filtering and judgment abilities, with medical background individuals better discerning information authenticity and preferring official platforms. These groups often functioned as "health information dissemination intermediaries," playing "core health communication circle" roles in families and communities.

Non-professionals exhibited information anxiety and dependence, showing strong motivation but often demonstrating "forwarding reliance," "experience-based judgments," or "rumor gullibility" when confronting complex health information.

5. **CONCLUSION**

This mixed-methods study provides comprehensive insights into health information dissemination mechanisms among middle-aged and elderly social media users in Changsha, China. The structural equation model demonstrates exceptional explanatory power, accounting for 92.3%, 81.5%, and 73.3% of variance in health information acquisition ability, rumor dissemination propensity, and cognitive processing ability, respectively.

Health information literacy emerges as the foundational cornerstone of the entire health

communication ecology. Its extraordinarily strong influence on cognitive processing ability (β = 0.856, f2 = 2.747) demonstrates that integrated traditional literacy, health literacy, and media literacy fundamentally shape older adults' information processing capabilities. This relationship creates cascading effects throughout the communication system, with literacy indirectly suppressing rumor dissemination through enhanced cognitive processing pathways.

Social support networks function as dual mechanisms, serving simultaneously as information facilitators and natural quality filters. The significant positive effect on information acquisition ability (β = 0.386) translates into substantial rumor suppression through mediation processes (β = 0.221), validating social capital theory's relevance in digital health contexts. However, qualitative findings reveal these networks can also amplify misinformation through homogeneous group dynamics.

Cognitive processing ability demonstrates multifaceted rumor suppression through direct effects (β = -0.589) and indirect pathways via enhanced information acquisition. The synergistic interaction with health information literacy (β = -0.031) reveals positive feedback loops essential for capacity building.

Qualitative analysis contextualizes statistical relationships within complex social realities, revealing integrated online-offline ecologies characterized by "authority orientation plus experiential verification" patterns. Information dissemination behaviors transcend mere transmission, encompassing group cohesion and care expression functions.

Critically, socioeconomic stratification creates structural boundaries conditioning information behaviors. Economic constraints limit premium resource access, while educational differences determine digital health literacy levels. Occupational backgrounds continue shaping cognitive schemas in digital environments.

The integration of quantitative precision with qualitative depth reveals health information dissemination among older adults as a complex adaptive system involving individual cognitive schemas, social network structures, economic constraints, and institutional supports. These findings challenge simplistic linear communication models, demonstrating the need for holistic approaches addressing structural inequalities while building individual capacities. The research provides theoretical foundations for understanding digital health communication among aging populations and practical guidance for designing targeted interventions to enhance information literacy and reduce rumor propagation.

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