Original Paper

Functional Preferences for Health-Promoting New Media Among Rural Residents: Cross-Sectional Discrete Choice Experiment

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Abstract

Background: Health-promoting new media can extend access to health information and education in rural communities. However, services need to accommodate residents' preferences for both communication features and practical requirements for use. Existing research on technology acceptance and disease-specific applications provides limited evidence about how rural residents weigh these features together when choosing services for general health promotion. Understanding these preferences can help guide locally appropriate digital service development.

Objective: This study aimed to quantify rural residents' stated preferences for functional attributes of health-promoting new media, explore preference variation, and identify priorities for services suited to rural community settings.

Methods: We conducted a cross-sectional discrete choice experiment in 3 townships in Guizhou Province, China, from August to October 2024. Adults with experience using new media were recruited through convenience sampling and completed face-to-face questionnaires. A literature review, expert consultation, and resident focus groups identified 6 attributes: operation mode, device type, information content, experience, information source, and daily time investment. The questionnaire was pretested with 20 residents before the main survey. Investigators provided standardized explanations and visual aids when needed to support comprehension. The experimental design included 24 choice tasks divided into 3 blocks. Each respondent completed 8 tasks, selecting between 2 hypothetical service profiles without an opt-out option. Conditional logit models estimated average preferences using respondent-clustered SEs. We report coefficients and 95% CIs. Daily time investment was modeled categorically, with 1 hour per day as the reference. Mixed logit models explored preference heterogeneity. Participants provided written informed consent.

Results: The analysis included 327 respondents who contributed 2616 choice occasions; 247 (75.5%) were women and 208 (63.6%) were aged 41 to 50 years. Most respondents had primary school education or below (n=198, 60.6%) and an annual household income per capita of ≤10,000 RMB (RMB 1=US $0.14035 as of October 31, 2024; n=194, 59.3%). Participants preferred voice or click operation over typing (β=–0.18, 95% CI –0.25 to –0.11), mobile phones over professional devices (β=–0.20, 95% CI –0.28 to –0.13), and basic over personalized content (β=–0.17, 95% CI –0.25 to –0.09). Daily time preferences were nonmonotonic: compared with 1 hour per day, 3 hours per day had lower utility (β=–1.06, 95% CI –1.52 to –0.60), whereas 5 hours per day had higher utility (β=0.25, 95% CI 0.16 to 0.34). Average preferences for experience and information source were not statistically significant. Supplementary mixed logit models yielded similar average preference estimates.

Conclusions: Mobile delivery, voice or click operation, and basic health information were preferred features among participants in this study. These findings identify priorities for developing and evaluating health promotion prototypes in comparable

communities. The nonmonotonic time pattern requires further investigation, and stated preferences should be evaluated against observed use. Convenience sampling limits the transferability of these findings to other rural populations.

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Keywords: digital health; rural residents; health-promoting new media; discrete choice experiment; user preferences

Introduction

Background

Mobile technologies can integrate health information, monitoring, and interventions into daily life, while their clinical benefits require evaluation [1]. The Lancet and Financial Times Commission places inclusion and governance at the center of digital health development [2]. A systematic review of randomized trials in adults with hypertension found improvements in blood pressure with digital interventions, although heterogeneity and risk of bias affected certainty [3]. Effective delivery also requires attention to engagement: users' observable participation and their cognitive and emotional experience are related but distinct dimensions [4]. The person-based approach therefore incorporates users' perspectives and everyday constraints into intervention development [5]. For rural health promotion, these perspectives motivate examining which functions residents value before selecting a service configuration. This is particularly relevant to digital health equity, which concerns the conditions under which different populations can benefit from technology [6].

Rural service development must account for unequal access to health care and digital resources. Research on China's primary health care system identifies continuing challenges in workforce capacity, quality, and coordination [7], and national surveys document disparities in preventive service coverage across urban-rural areas and income groups [8]. Digital health equity frameworks locate access within individual, interpersonal, community, and societal conditions [6]. Digital health literacy also extends beyond operating a device to understanding and using digitally mediated information [9]. Equity-focused implementation consequently requires attention to both technological and social conditions [10,11]. These findings support considering familiar equipment, understandable interaction, and available support together. Our study addresses the corresponding design question: which functional requirements do rural residents favor when selecting among alternative health-promotion services?

In this study, health-promoting new media refers to digitally enabled platforms, devices, and content formats used to deliver health information, education, and support for health-related engagement or behavior change. AI contributes to the technological context, including capabilities and limitations in answering medical questions [12]; our focus is on user-facing functions rather than AI itself. We examine 6 attributes: operation mode, device, information content, information source, experience, and daily time investment. Operation mode describes navigation or input actions; experience describes the bundled interactivity, entertainment, and scenario-based presentation offered to respondents. Device identifies the equipment used, content distinguishes basic from personalized information, source identifies its provider, and time specifies daily participation requirements. These distinctions allow us to examine communication features alongside the practical demands of accessing them. This approach is consistent with person-based development and engagement research, which emphasize the interaction between intervention characteristics and users' contexts [4,5,13].

The Medical Research Council framework for complex interventions emphasizes context, stakeholder perspectives, and uncertainties relevant to development and implementation [14]. Preference studies can inform such decisions: Xie and Or [15] examined purchasing choices for mobile health apps, while Hewage et al [16] investigated app features for people with chronic heart disease. These studies provide evidence about specific products and disease-management needs. Our question concerns general health promotion in rural communities, where equipment, operation, content, source, experience, and time must be considered within the same service configuration. Rather than asking only whether residents welcome digital health, we examine which attributes influence their choices among competing configurations. This contextual focus complements existing application research and can help specify the functions to prioritize in local development.

Discrete choice experiments (DCEs) estimate the contributions of attribute levels to relative preference by presenting alternatives that vary across several characteristics [17]. Design and reporting guidance emphasize meaningful attributes, appropriate choice tasks, and transparent analysis [18,19]. We applied this approach among rural adults with new-media experience in Dushan County, Guizhou Province, China. The primary objective was to estimate average preferences for the 6 functional attributes; supplementary analyses examined sensitivity and heterogeneity. By evaluating communication features alongside access and time requirements, the study aims to translate rural residents' choices into priorities for prototype development. The intended contribution is evidence for locally appropriate design, with actual use and health outcomes to be evaluated during implementation.

Theoretical Framework for Interpretation

Overview

Four complementary perspectives inform our interpretation: the Unified Theory of Acceptance and Use of Technology (UTAUT), the Elaboration Likelihood Model (ELM), Protection Motivation Theory (PMT), and Social Presence Theory. Attributes were developed through a literature

review, expert consultation, and discussions with rural residents. The perspectives below connect access requirements, communication features, experience, and participation demands to the study's functional comparisons.

UTAUT

UTAUT links technology acceptance and use to performance expectancy, effort expectancy, social influence, and facilitating conditions [20]. UTAUT2 adds enjoyment, price value, and habit to account for consumer settings [21]. In our functional interpretation, operation mode represents the actions needed to use a service, while device identifies its equipment requirements. Digital equity research reinforces the importance of considering these resources alongside intended benefits [6,11]. This provides a rationale for examining equipment and interaction within the same choice as content and experience.

Where UTAUT-based research models acceptance and use [20,21], our DCE estimates preferences among specific configurations. It therefore complements adoption-intention research by identifying design-level trade-offs rather than measuring a general willingness to use technology. The forced choices assess relative preference between offered services; they do not estimate uptake when nonuse is possible [17,19]. This distinction keeps the contribution focused on selecting features for development.

ELM

ELM explains how motivation and ability shape the processing of message arguments and contextual cues [22,23]. Evidence on tailored print health communication supports the potential value of personal relevance [24], while a systematic review identifies varied approaches to digital personalization [25]. These findings motivate considering information content and source separately. In this study, they represent what information is offered and who provides it, rather than a combined measure of information quality.

ELM provides an interpretive basis for examining communication features alongside access requirements. The contribution is to estimate the relative appeal of basic or personalized content and different providers within otherwise specified services. As the influence of arguments and cues depends on recipients' involvement [23], we do not assign personalized content exclusively to central processing or source exclusively to peripheral processing. Our comparisons concern functional preferences, not measured processing routes.

PMT

PMT distinguishes threat appraisal from coping appraisal, including response efficacy, self-efficacy, and response costs [26,27]. A meta-analysis found that greater efficacy beliefs and lower response costs generally favored adaptive intentions or behaviors [27]. We use this perspective to consider the demands of participating in digital health communication. Daily time, operation, and equipment describe practical requirements, although they are not direct measures of coping appraisal.

This perspective helps frame the study's comparison of communication features and participation demands. Within the DCE, time varies alongside content and experience, allowing its contribution to relative preference to be estimated. PMT's attention to efficacy and costs [26,27] motivates considering the value of participation alongside its demands. Our purpose is to inform manageable service configurations rather than test protection motivation or predict protective behavior.

Social Presence Theory

Social Presence Theory concerns the sense of another person and interpersonal connection in mediated communication [28,29]. Research distinguishes this experience from immersion and the sense of being in a virtual place [30]. Our experience attribute bundles interactivity, immersion, and perceived presence; it is therefore broader than social presence alone. Reviews of engagement strategies and social support also show the importance of intervention components and context [31,32]. These perspectives motivate evaluating experiential features in relation to the communication task.

Separating operation mode from experience allows us to distinguish how users control a service from what they encounter through it. Social presence research indicates that technical richness alone does not determine the communication experience [29,30]. Our design examines experience alongside equipment, input, and time, bringing experiential value and practical access into the same comparison. Together, the 4 perspectives guide interpretation of the attribute estimates and their design implications; the main-effects analysis does not test psychological pathways or functional synergies.

Research Gap and Objectives

Previous DCEs have examined preferences for health app purchasing and disease-specific self-management [15,16], while technology acceptance frameworks have focused on explaining adoption intentions and use [20,21]. Less is known about how rural residents weigh different functional features when choosing new media for general health promotion. Addressing this gap requires examining preferences for specific service configurations rather than willingness to adopt a technology alone. This study therefore used a DCE among rural adults with new-media experience in a county in China to quantify stated preferences for 6 attributes: mode of operation, device type, information content, experience, information source, and daily time investment. Specifically, we aimed to estimate how different attribute levels influenced choices, explore variation in preferences among respondents, and identify preferred features to inform the design of health-promoting new media for rural communities.

Methods

Study Design, Setting, and Participants

This cross-sectional study used a DCE, grounded in random utility theory, to quantify rural residents' preferences for

functional features of health-promoting new media [17,33]. The survey was conducted in villages located in 3 townships in Dushan County, Guizhou Province, western China, between August and October 2024. Convenience sampling was adopted because of constraints in research resources, time, and staffing, together with practical considerations regarding access and fieldwork feasibility in rural areas. With assistance from township health centers, village clinics, and village committees, trained investigators approached potentially eligible residents who were accessible during the survey period, explained the study, screened them against the eligibility criteria, and invited all eligible individuals who were willing to participate. Eligibility criteria were being aged 18 years or older, residing in a rural area, having sufficient communication and comprehension abilities to complete the survey, having experience using new media, and being able to provide informed consent. Individuals who did not meet these criteria or declined participation were not enrolled. Face-to-face interviews were conducted in community locations or participants' households, with standardized clarification and visual aids provided when needed. During fieldwork, the team observed that women were more often available at home, whereas many men were away for migrant employment, which may partly explain the predominance of women in the sample.

Pretesting and Cognitive Interviews

Before the main survey, the questionnaire was pretested with 20 rural residents drawn from the target population who did not subsequently participate in the main survey. The pretest assessed the comprehensibility of the attributes and levels, the clarity of the instructions and choice scenarios, the cognitive burden of the tasks, and the usability of the visual materials. Cognitive interviews were conducted using think-aloud and verbal probing techniques to explore how participants interpreted the attribute descriptions and made their choices. Based on participant feedback, technical terminology was replaced with plain-language expressions, the wording of several attribute levels was revised, and images and videos were added to illustrate professional smart devices and immersive experiences. An example and a practice choice task were also added, the instructions were shortened and reordered, and investigators were provided with standardized explanations. Pretest data were used solely to refine the questionnaire and were excluded from the final analysis. The DCE elicited discrete choices rather than a composite psychometric score, so internal consistency coefficients were not used.

Sample Size and Precision

The minimum sample size was estimated using the Johnson-Orme rule of thumb (Equation 1), where c denotes the maximum number of levels for any attribute, t the number of choice tasks per respondent, and a the number of alternatives per task. With c=3, t=8, and a=2, the heuristic yields approximately 94 respondents. Because it does not fully account for parameter precision or preference heterogeneity [34], a larger sample of approximately 350 was targeted, with repeated choices and possible heterogeneity in mind. Reviews describe substantial variation in sample sizes and heterogeneity analyses across health care DCEs [35,36]; these observations do not establish power for this study. The final analysis focuses on average preferences. Repeated tasks are not treated as independent respondents, and uncertainty is reported using CIs rather than a claim of adequate power for every comparison.

$$\frac{Nta}{c} \geq 500 \quad (1)$$

Attribute Development

Attributes were selected through a 3-step process: (1) a literature review of studies on digital health interventions, health communication, and technology acceptance to identify commonly reported determinants of use; (2) expert consultation with scholars in public health, health management, and information technology to refine attributes for contextual relevance; and (3) focus group discussions with rural residents to ensure that the attributes and levels were understandable and reflected lived experience.

Six attributes were finalized through this process.

For clarity and reproducibility, Table 1 presents each attribute's operational definition, complete set of levels, reference category, and coding used in estimation.

Table 1. Attributes, operational definitions, levels, and coding used in the discrete choice experiment.[a]

Attribute	Operational definition	Levels included in the DCE[b]	Reference category/coding
Mode of operation	Input mechanism used to navigate the platform, enter information, or issue commands	Typing; voice or click	Voice or click=0 (reference); typing =1
Device	Physical device used to access and interact with the platform	Professional smart device; mobile phone	Mobile phone=0 (reference); professional smart device=1
Information content	Degree to which the health information is general or tailored to individual needs	Basic information; personalized information	Basic information=0 (reference); personalized information=1
Information source	Organization or person presented as providing or endorsing the health information	Government health department; specialist doctor; peers	Government health department=reference; doctor and peers represented by separate dummy variables
Experience	Composite of interaction, entertainment, and scenario-based presentation	Low presence: less interaction and entertainment, with text, video, or images; high presence: more interaction	Low presence=0 (reference); high presence=1

Attribute	Operational definition	Levels included in the DCE[b]	Reference category/coding
		and entertainment, with interactive scenarios similar to a live broadcast	
Time investment	Daily time required to use the platform or engage with its health content	1, 3, or 5 h/d	1 h/d (reference); separate indicators for 3 and 5 h/d

[a]This table presents the attribute and level specifications for a discrete choice experiment of functional preferences for health-promoting new media among rural residents in Guizhou Province, China, surveyed from August to October 2024.
[b]DCE: discrete choice experiment.

Variables and Measures

Mode of Operation

Mode of operation refers specifically to the input mechanism through which users navigate a digital health platform, enter information, or issue commands. In this study, it distinguishes typing-based input from voice- or click-based operation and therefore reflects the effort and technical skills required for human-device interaction. This distinction is particularly relevant to rural users who may experience literacy, visual, or digital literacy barriers. Voice-based systems, such as interactive voice response, can improve comprehension and engagement among people with low literacy [37]. Although visual interventions, such as videos, may also improve understanding of health information [38], they concern the presentation of content rather than the mechanism used to control the platform and were therefore conceptually captured under the experience attribute. Research on digital health literacy further indicates that simpler interaction mechanisms are associated with greater engagement with health resources [39,40], while voice assistants may support more intuitive self-management among populations with limited digital literacy [41].

Type of Device

Device access is a critical determinant of digital health use. Recent evidence shows that while smartphones are the dominant access device in rural and underserved populations, other devices such as desktop or laptop computers, tablets, and televisions remain in use, particularly among older adults and in households where devices are shared [42-44]. Device type further shapes the feasibility of interactive functions and the richness of visual presentation, thereby influencing user engagement and usability in digital health interventions [45].

Content of Information

The relevance of health information content is central to motivating adoption. Recent studies show that rural and underserved populations tend to prioritize preventive health information, chronic disease self-management, and practical lifestyle guidance when engaging with digital health tools [46,47]. Evidence further indicates that tailored, context-specific, and practically relevant content enhances adherence and sustained engagement with digital health interventions, particularly among populations facing resource or literacy constraints [3,48].

Source of Information

Source credibility is a key determinant of trust in digital health. Recent evidence indicates that health information originating from government agencies and medical professionals is consistently perceived as more trustworthy than information from commercial platforms or peer-based online communities [49,50]. Source credibility, in turn, plays a central role in message acceptance and sustained engagement with digital health interventions, particularly in contexts where misinformation and variable information quality coexist [51].

Experience

Experience was operationalized as a composite of interaction, entertainment, and presentation context. The high-presence level described more interaction with others, greater entertainment, and interactive scenarios such as exercise scenes, similar to a live broadcast. The low-presence level described less interaction, lower entertainment, and text, video, or images without those interactive scenarios. Thus, the attribute did not isolate immersion or social presence alone. Operation mode, in contrast, described how users entered information or controlled the platform. Reviews of interactive and immersive formats report potential benefits for learning and engagement [52-54], but the present composite measures relative preference for the bundled descriptions rather than the separate effects of their components.

Time Investment

The time required to engage with digital health content influences usability and adoption. Evidence suggests that intervention design features, including content complexity, modularity, and burden of use, are among key predictors of adherence to digital health technologies [55]. Research further indicates that elements associated with easier engagement, such as concise, modular content and reduced time demands, correlate with higher usage and lower dropout [13,56]. In contrast, interventions with higher time costs or longer sessions are frequently associated with lower engagement and increased attrition [13].

Experimental Design

A D-efficient fractional factorial design was generated using Ngene (ChoiceMetrics) under a multinomial logit framework, following established good-practice principles for DCE experimental design [18]. Because reliable prior estimates were unavailable, fixed null priors of 0 were specified for

all parameters; therefore, a Bayesian efficient design was not used. The categorical attributes were dummy coded. One parameter was specified for each binary attribute, 2 parameters were specified for the 3-level information-source attribute, and time investment was specified continuously at the design stage. The reported design-efficiency statistics refer to this original design model; categorical-time estimation was added during the statistical revision.

The final design comprised 24 choice sets divided into 3 blocks of 8 tasks each. Participants were randomly assigned to 1 block and completed 8 choice tasks. Each task presented 2 hypothetical health-promoting new media alternatives without an opt-out option. The final design yielded a D-error of 0.14 and an A-error of 0.19. A repeated choice task was additionally included to assess response consistency and was excluded from the main preference analysis. The forced-choice format elicits relative preference between the 2 displayed configurations. This is consistent with the study's focus on functional trade-offs, but respondents could not reject both options or retain their current practice. Accordingly, choice probabilities are conditional on the offered alternatives and should not be interpreted as probabilities of real-world uptake [19].

Survey Administration

The questionnaire collected sociodemographic characteristics, health status, and indicators of new-media use. Investigators followed standardized instructions, provided standardized explanations of the attributes and levels, and checked questionnaires for completeness after each interview. A repeated task with an identical attribute-level configuration was included to assess response consistency.

Data Quality, Participant Flow, and Missing Data

Of 350 questionnaires collected, 22 were excluded during questionnaire-level quality assessment. One additional questionnaire was excluded for inconsistent responses to the repeated identical choice task. All exclusions applied to both descriptive and choice-model analyses. The final sample contained 327 respondents, 2616 analyzed choice occasions (327 × 8), and 5232 alternative-level records (327 × 8 × 2). Each analyzed task contained 2 alternatives and 1 selected option. The 24 formal task profiles across the 3 questionnaire versions were checked against the analysis workbook; the example and repeated consistency task were not included in model estimation.

Statistical Analysis

Descriptive statistics summarized sociodemographic and health-related characteristics. The choice-model variables in the verified analysis workbook contained no missing values. Tests were 2-sided with α=.05, and estimates are reported with 95% CIs. Under random utility theory, utility for respondent i choosing alternative j in task t was specified in Equation 2. Conditional on the coefficients, the alternative-specific errors were assumed to follow independent type I extreme-value distributions.

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} V_{ijt} = \beta_1 \text{Typing}_{ijt} + \beta_2 \text{ProDevice}_{ijt} + \beta_3 \text{Personalized}_{ijt} + \beta_4 \text{HighPresence}_{ijt} + \beta_5 \text{Doctor}_{ijt} + \beta_6 \text{Peer}_{ijt} + \beta_7 \text{Time3}_{ijt} + \beta_8 \text{Time5}_{ijt} \quad (2)$$

The unlabeled alternatives had no alternative-specific constant. Nontime attributes were dummy-coded using voice or click operation, mobile phone, basic information, low presence, and government source as references, with separate doctor and peer indicators. Time was represented by indicators for 3 and 5 hours per day, relative to 1 hour per day, in the revised primary model. In Equation 2, Typing=1 indicates typing rather than voice or click operation, and ProDevice=1 indicates a professional smart device rather than a mobile phone; both variables equal 0 at their respective reference levels. Time3 and Time5 denote the time indicators. A continuous-time specification was compared with this model using the linearity restriction $\beta_8=2\beta_7$. The conditional logit model (CLM) used unique respondent-task strata and respondent-clustered sandwich SEs. The mixed logit model (MXL) assigned independent normal distributions to the 6 nontime coefficients, constant across each respondent's 8 tasks; the 2 time coefficients were fixed. Random-time specifications were examined as sensitivity analyses.

Stata 17 estimated the reported CLM and MXL. The MXL used simulated maximum likelihood with 1000 Halton draws per respondent after a burn-in of 100, integrating each respondent's product of task probabilities. The CLM is the homogeneous-coefficient special case. Models used the same sample, choices, and likelihood normalization. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) were calculated from the log-likelihood (LL) as AIC=$-2LL+2k$ and BIC=$-2LL + k \ln(N)$, with k counting all free preference, scale, and membership parameters and 327 independent respondents. The categorical-time CLM was selected as primary during revision based on the linearity test and information criteria. MXL signed normal scales are reported separately from means; their absolute values are distributional SDs, but reported scale CIs remain on the signed estimation scale [57]. Sensitivity checks used 500 and 2000 Halton draws for linear-time MXL; independent scrambled-Halton implementations also compared 1000 and 2000 draws for categorical time and allowed time coefficients to vary. Python/SciPy checks used seed 20260922, skipped 100 points, and used 2 initial scale values per MXL specification.

Exploratory panel latent class logit models with 2, 3, and 4 classes were estimated from 30 initializations per class count in Python/SciPy. The 6 nontime coefficients varied by class, the 2 categorical-time coefficients were shared, and class-membership probabilities were intercept-only. The 1-class benchmark was the CLM. Linear-time variants were also examined. Model evaluation considered LL, AIC, BIC, convergence, extreme coefficients, and the information matrix rather than information criteria alone. For observed heterogeneity, separate pooled CLMs interacted all 8 attribute indicators, including categorical time, with age group, chronic disease status, or self-rated health. Age groups were 21 to 30, 31 to 40, 41 to 50, and 51 years or older; the 2 poorest health categories were combined. Respondent-clustered joint Wald tests assessed all interaction terms for each grouping, with

Holm adjustment across the 3 global tests. These revision-stage analyses were exploratory; logit coefficient differences can also reflect differences in error scale. Independent Python calculations checked the Stata estimates.

Ethical Considerations

Ethical approval was obtained from the Institutional Review Board of Huazhong University of Science and Technology (approval [2023]IEC(A150)). Written informed consent was obtained from all participants before data collection. All study data were anonymized before analysis, and confidentiality was protected throughout the study. Participants received no financial or other compensation for participation. No images in the manuscript or supplementary materials contain information that could identify individual participants or users.

Results

Descriptive Statistical Analysis

Participant characteristics are shown in Table 2. Women comprised 75.5% (247/327) of respondents; 63.6% (208/327) were aged 41 to 50 years, and 60.6% (198/327) had primary school education or below. Most respondents were married (278/327, 85.0%) and insured (290/327, 88.7%). Annual household income per capita was ≤10,000 RMB (RMB 1=US $0.14035 as of October 31, 2024) for 59.3% (194/327). Seventy-one respondents (71/327, 21.7%) reported chronic disease. Self-rated health was good in 66.1% (216/327), fair in 30.0% (98/327), and poor in 4.0% (13/327) after combining the 2 poorest categories. Participant flow and exclusions are summarized in Figure 1.

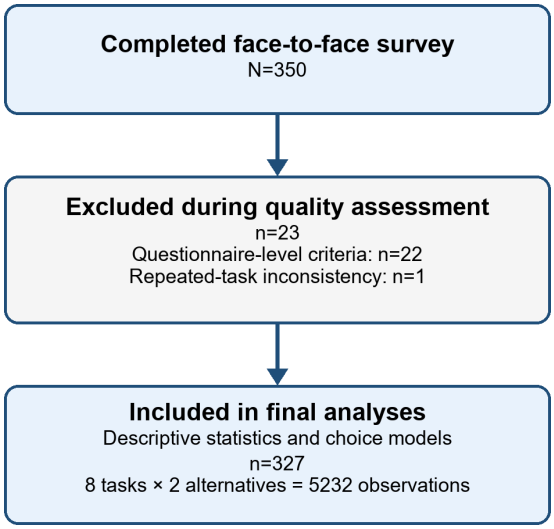
Table 2. Demographic and health-related characteristics of respondents (n=327).[a]

Characteristics	Participants, n (%)
Gender	
Male	80 (24.5)
Female	247 (75.5)
Age (y)	
21-30	38 (11.6)
31-40	43 (13.1)
41-50	208 (63.6)
51 and above	38 (11.6)
Marital status	
Married	278 (85.0)
Unmarried/divorced/widowed	49 (15.0)
Education	
Primary school or below	198 (60.6)
Secondary/technical school	108 (33.0)
College or above	21 (6.4)
Medical insurance	
Yes	290 (88.7)
No	37 (11.3)
Annual household income per capita (RMB/person/y)[b]	
≤5000	91 (27.8)
5001-10,000	103 (31.5)
10,001-30,000	87 (26.6)
≥30,001	46 (14.1)
Chronic disease	
No	256 (78.3)
Yes	71 (21.7)
Self-rated health	
Good	216 (66.1)
Fair	98 (30.0)
Poor	13 (4.0)

[a]The sample consists of rural residents with new-media experience recruited by convenience sampling in Dushan County between August and October 2024.

[b]Income is the respondent-reported annual household income per capita category, not total household income; it was not explicitly measured as disposable income. RMB 1=approximately US $0.14035 as of October 31, 2024 (US $1=RMB 7.1250).

Figure 1. Participant flow through the cross-sectional discrete choice experiment (DCE). The analyzed DCE sample included rural residents in Guizhou Province, China, surveyed from August to October 2024. The DCE contained 8 choice tasks per respondent and 2 alternatives per task.



Average Stated Preferences

Conditional Logit Estimates

In the categorical-time CLM (Table 3), relative utility was lower for typing than voice or click (β=–0.18, 95% CI –0.25 to –0.11), professional devices than mobile phones (β=–0.20, 95% CI –0.28 to –0.13), and personalized than basic content (β=–0.17, 95% CI –0.25 to –0.09; all *P*<.001). Relative to 1 hour per day, 3 hours had lower utility (β=–1.06, 95% CI –1.52 to –0.60) and 5 hours had higher utility (β=0.25, 95% CI 0.16 to 0.34; both *P*<.001). Thus, the time pattern was not monotonic. CIs included 0 for high presence (β=0.01, 95% CI –0.06 to 0.09), specialist-doctor information (β=0.05, 95% CI –0.06 to 0.16), and peer information (β=0.05, 95% CI –0.06 to 0.15).

Table 3. Conditional logit estimates with respondent-clustered SEs (n=327).[a]

Attribute contrast	β/scale (95% CI)	SE	*z*	*P* value
Typing vs voice or click	–0.18 (–0.25 to –0.11)	0.04	–4.73	<.001
Professional device vs mobile phone	–0.20 (–0.28 to –0.13)	0.04	–5.19	<.001
Personalized vs basic content	–0.17 (–0.25 to –0.09)	0.04	–4.08	<.001
High vs low presence	0.01 (–0.06 to 0.09)	0.04	0.36	.72
Specialist doctor vs government	0.05 (–0.06 to 0.16)	0.06	0.90	.37
Peer vs government	0.05 (–0.06 to 0.15)	0.05	0.91	.36
3 vs 1 h/d	–1.06 (–1.52 to –0.60)	0.24	–4.48	<.001
5 vs 1 h/d	0.25 (0.16 to 0.34)	0.05	5.28	<.001

[a]References are named in each row. Negative coefficients for typing, professional devices, and personalized content indicate lower utility than voice or click operation, mobile phones, and basic content, respectively. Time contrasts are 3 and 5 h/d versus 1 h/d. The 327 respondents contributed 2616 binary tasks and 5232 alternative records. CIs and *P* values use respondent-clustered sandwich SEs.

The supplementary categorical-time MXL had similar mean coefficients (Table 4). Most non–time scale estimates were close to 0. The doctor-source signed scale was 0.29 (95% CI 0.04 to 0.55), suggesting possible variation under this specification. These conventional scale intervals are not boundary-adjusted variance-component tests, and the MXL's information criteria did not improve on the CLM. Average source preferences and individual variation are therefore interpreted separately.

Table 4. Mixed logit mean coefficients and signed normal scale parameters (n=327).[a]

Attribute contrast	β/scale (95% CI)	SE	*z*	*P* value
Mean coefficients				
Typing vs voice or click	–0.18 (–0.27 to –0.10)	0.04	–4.30	<.001
Professional device vs mobile phone	–0.21 (–0.29 to –0.12)	0.04	–4.77	<.001
Personalized vs basic content	–0.17 (–0.26 to –0.09)	0.04	–4.09	<.001
High vs low presence	0.02 (–0.06 to 0.10)	0.04	0.44	.66
Specialist doctor vs government	0.05 (–0.07 to 0.17)	0.06	0.82	.41
Peer vs government	0.05 (–0.07 to 0.16)	0.06	0.82	.41
3 vs 1 h/d	–1.09 (–1.59 to –0.59)	0.26	–4.28	<.001
5 vs 1 h/d	0.25 (0.15 to 0.35)	0.05	4.89	<.001
Signed normal scale parameters				

Attribute contrast	β/scale (95% CI)	SE	*z*	*P* value
Typing vs voice or click	0.00 (–0.18 to 0.18)	0.09	0.00	>.99
Professional device vs mobile phone	0.00 (–0.26 to 0.26)	0.13	0.01	.99
Personalized vs basic content	0.01 (–0.48 to 0.49)	0.25	0.02	.98
High vs low presence	0.00 (–0.23 to 0.23)	0.12	0.00	>.99
Specialist doctor vs government	0.29 (0.04 to 0.55)	0.13	2.28	.02
Peer vs government	0.00 (–0.41 to 0.42)	0.21	0.01	.99

[a]The mixed logit model used 1000 Halton draws per respondent after a burn-in of 100. The 6 nontime coefficients were independently normally distributed. The 2 categorical-time coefficients were fixed and have no random scale parameters. Absolute signed scale estimates correspond to distributional SDs; SEs and CIs in the lower panel remain on the signed scale. These Wald intervals are not boundary-adjusted tests of zero variance.

Supplementary Mixed Logit and Model Fit

With categorical time, the CLM LL was −1770.15 and the MXL LL was −1769.38, compared with −1813.27 at zero coefficients. The CLM had lower AIC and BIC than the MXL and than either linear-time model (Table 5). The linearity restriction was rejected in both the CLM (cluster-robust Wald χ^2_1=24.76, *P*<.001) and MXL (χ^2_1=23.38, *P*<.001).

Table 5. Fit statistics for the reestimated choice models.[a]

Model	LL[b]	*k*	AIC[c]	BIC[d]
CLM[e] categorical time	−1770.15	8	3556.29	3586.61
MXL[f] categorical time	−1769.38	14	3566.76	3619.82
CLM linear time	−1782.89	7	3579.77	3606.30
MXL linear time	−1782.44	13	3590.88	3640.15

[a]All models used 327 respondents, 2616 choice occasions, and 5232 alternative records. *k* counts all free coefficients, including the 6 mixed logit model scales. Bayesian information criterion uses the same independent-respondent n value for all models.
[b]LL: log-likelihood.
[c]AIC: Akaike information criterion.
[d]BIC: Bayesian information criterion.
[e]CLM: conditional logit model.
[f]MXL: mixed logit model.

Sensitivity and Heterogeneity Analyses

Changing linear-time MXL simulation from 500 to 2000 Halton draws left the average coefficients closely aligned. Independent categorical-time MXL estimates differed by less than 0.01 between 1000 and 2000 scrambled-Halton draws. Allowing the continuous-time coefficient to vary produced AIC=3592.87 versus 3590.88 with fixed time. In the independent categorical-time comparison, allowing both time indicators to vary produced AIC=3570.65 versus 3566.73 with fixed time. These checks support the simpler specifications without proving that time preferences are homogeneous (Table 6).

Table 6. Latent class estimation diagnostics with categorical time.

Classes	*k*	Best LL[a]	AIC[b]	BIC[c]	Highest-LL solution
1	8	−1770.15	3556.29	3586.61	CLM[d] benchmark
2	15	−1716.29	3462.59	3519.43	Extreme coefficients; near-singular information
3	22	−1682.65	3409.29	3492.67	Extreme coefficients; near-singular information
4	29	−1654.27	3366.55	3476.46	Extreme coefficients; near-singular information

[a]LL: log-likelihood.
[b]AIC: Akaike information criterion.
[c]BIC: Bayesian information criterion.
[d]CLM: conditional logit model.

Table 7 presents the exploratory joint tests of attribute-by-group interactions. The joint test of interactions between attribute levels and age group was statistically significant before adjustment (χ^2_{24}=39.90, *P*=.02), but not after Holm adjustment for multiple testing (adjusted *P*=.07). The corresponding tests for chronic disease status (χ^2_8=10.02, adjusted *P*=.53) and self-rated health (χ^2_{16}=14.36, adjusted *P*=.57) were also not statistically significant. Thus, after accounting for multiple testing, these analyses did not provide sufficient evidence that preferences differed by age group, chronic disease status, or self-rated health (Table 7).

Table 7. Exploratory joint tests of attribute-by-group interactions.

Grouping	Chi-square (*df*)	*P* value	Holm *P*
Age (4 groups)	39.90 (24)	.02	.07
Chronic disease (2 groups)	10.02 (8)	.26	.53
Self-rated health (3 groups)	14.36 (16)	.57	.57

Discussion

Principal Findings

This study identifies functional preferences that can inform the design of health-promoting new media for rural communities. Respondents preferred mobile phones to professional smart devices, voice or click operation to typing, and basic to personalized health information. Considered together, these findings support a design emphasis on mobile access, reduced dependence on text entry, and a clearly organized foundation of health information. The contribution is particularly relevant to community health promotion, where the task is to make useful information approachable in everyday life. By eliciting choices between complete media configurations, the study translates broad calls for user-centered digital health into specific decisions about how a service is accessed, operated, and organized.

Device Access and Ways of Interacting

The preference for mobile phones supports prioritizing phone-based delivery for general health information in this setting. Mobile technologies can connect health activities with everyday communication [1], while a review of rural telemedicine identifies barriers across products, users, providers, infrastructure, and policy [58]. Our finding contributes a specific equipment preference to this broader implementation literature. Developers can begin with core mobile functions and consider additional hardware for tasks with defined technical requirements. The device finding also gives a concrete application to technology-acceptance and digital-equity perspectives. UTAUT emphasizes effort expectancy and facilitating conditions alongside expected usefulness [20]. From this perspective, the appeal of a health platform includes the practical work needed to reach and operate it. Digital health equity frameworks likewise place technology access within a wider set of individual and social conditions [6]. The present preference evidence brings these concerns into the design of rural health communication: choosing the delivery device is part of designing access, not merely a hardware decision. A phone-based approach can therefore be developed together with clear navigation, appropriate language, and community support, aligning the means of delivery with the setting in which information will be used. Voice or click operation complements mobile delivery by reducing the text entry required in the offered alternative. With primary-school education or below common in this sample, the finding identifies a relevant interface priority. Co-design research with older adults similarly emphasizes adapting voice assistants to health-management tasks, user context, and autonomy [41]. Drawing on our preference results, we propose prominent buttons, direct topic selection, and voice-enabled access as prototype features, with optional typing for detailed questions.

Information Content and Communication Experience

The preference for basic information supports making foundational health knowledge and behavioral advice the core of a general health-promotion service. This contrasts with a chronic heart disease DCE in which the larger class placed greater value on tailored than generalized education [16]. The difference points to a useful question about service purpose and population. Reviews identify diverse personalization approaches [25] and variable effects across workplace mental health populations and outcomes [59]. Our results add rural community preference evidence to this literature and support selecting personalization for a defined information need. Basic information may offer a recognizable starting point for exploring health concerns. This interpretation is consistent with ELM's emphasis on motivation and ability in processing messages [22,23], rather than evidence that a particular processing route operated here. We propose organizing core messages clearly and offering additional tailored guidance for specific questions. This gives the observed preference a practical application while retaining opportunities for more individualized support.

Information-source estimates did not establish a clear average preference for specialist-doctor or peer information over government information. Research on electronic health data links trust with privacy and attitudes toward data use [60], illustrating dimensions of trust beyond a provider's label. A practical approach is therefore to state each source clearly and distinguish public guidance, clinical explanations, and personal experiences. These are complementary service-design proposals, not a source ranking inferred from the nonsignificant estimates. Higher presence likewise showed no clear average preference advantage. Reviews distinguish social presence from technical richness and show that communication experiences depend on users and context [28,29]; digital intervention reviews also identify variation in engagement and social-support effects [31,32]. For development, we suggest choosing interactive features for specific purposes, such as demonstrating an action or answering a question. The results leave room for purposeful interaction without making elaborate experiences the default priority.

Time Demands and Everyday Use

Time preferences showed a nonmonotonic pattern: 3 hours per day was less preferred than 1 hour per day, whereas 5 hours per day was more preferred. The observed coefficients do not follow a simple linear relationship, supporting the use of categorical time indicators and motivating

further investigation of how different time requirements are understood. The available data do not reveal the reason for this pattern because perceptions of expected value, benefits, scope, and the practical meaning of the daily time requirement, as well as reasons for choosing a profile, were not measured. We therefore interpret these coefficients as relative evaluations of the hypothetical profiles and do not attribute them to a specific behavioral mechanism. PMT provides a useful conceptual context in which response costs may be considered alongside efficacy-related appraisals [26,27], but these appraisals were beyond the scope of this study. The findings can inform the design of follow-up studies and prototype testing, while future research should compare more realistic time levels and assess flexible formats, such as a brief core message with optional additional material, that allow users to control the depth and pace of participation [4,61].

New Insights

The study extends preference research on app purchasing and chronic disease self-management [15,16] to general health promotion in a rural community setting. Its innovation lies in evaluating access, communication, and time requirements together within complete service choices. Compared with broad acceptance frameworks [20,21], it supplies attribute-level evidence for specific design decisions. The favored levels indicate that convenient digital access can coexist with a preference for basic information, identifying a candidate configuration for local prototype development. This contribution emphasizes functional fit rather than adding features by default. Technology acceptance, information processing, response costs, and social presence offer complementary interpretive perspectives [20,22,27,29]. Applied here, they connect equipment and operation to communication content and participation demands. The resulting contribution is a locally grounded set of design priorities, not a universal ranking of technologies: mobile access, low-text-input interaction, and a strong foundation of health information.

Practical Implications

For developers, the findings support beginning with a phone-based prototype that provides voice or click access to clearly organized basic health information. Optional tailored guidance can address specific questions. Person-based development emphasizes iterative work with intended users [5]; accordingly, testing should assess comprehension, task completion, navigation errors, and satisfaction. Preference evidence can guide which features receive initial development resources, while usability testing determines how well those features work in practice. For local providers, we propose connecting the service with township health centers and village clinics, which could select topics, introduce core functions, and direct questions to appropriate professionals. This is consistent with Chinese digital health governance research emphasizing institutional coordination, locally adapted implementation, and privacy protection [62]. Clear responsibility for content review, updates, and user feedback would give the proposed service an operational place within community health promotion. AI can be considered as an implementation option where it serves these priorities. Reviews describe digital-health chatbots and AI-supported interventions for information provision and tailored support [63,64]. In a future prototype, these capabilities could support voice access or optional guidance, with content review, privacy protection, and appropriate oversight [62-64]. Our contribution concerns the functions residents prefer, providing design direction without attributing their preferences to AI.

Limitations

The convenience sample was drawn from 3 townships in one county and predominantly comprised middle-aged women with new-media experience, limiting transferability. The forced hypothetical choices estimate relative preferences rather than actual adoption or health outcomes [19]. Device costs and ownership were not measured, and the intensive time levels limit direct app to everyday use. Voice and click operation and several aspects of experience were bundled, preventing estimation of their separate contributions. Future work should broaden recruitment, separate bundled functions, use more practical time levels, and link preference-informed prototypes to observed use and health-related outcomes. These extensions would build on the functional priorities identified here.

Conclusions

This study provides preference-based guidance for developing health-promoting new media in rural communities. Mobile phones, voice or click operation, and basic health information emerged as favored features within the offered configurations. The findings support a phone-based, low-text-input service with a clear foundation of health content and selectively added functions. Its main contribution is to translate rural residents' choices into concrete priorities for digital health design, complementing research on general technology acceptance. Combining these priorities with community-based delivery and user-centered development offers a practical direction for making digital health information more approachable and relevant to rural life. The nonmonotonic time estimates remain unexplained by the available data and do not justify prescribing a daily duration.

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Generative AI Use

The authors declare the use of generative AI (GenAI) in the research and writing process. According to the GAIDeT taxonomy (2026), the following tasks were delegated to GenAI tools under full human supervision: feasibility assessment and risk evaluation; literature search and systematization; proofreading and editing; adapting and adjusting emotional tone; and translation. The GenAI tool used was ChatGPT (GPT-5.6 Terra; OpenAI). Responsibility for the final manuscript lies entirely with the authors. GenAI tools are not listed as authors and do not bear responsibility for the final outcomes. Declaration submitted by QW, ZF, XZ.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Authors' Contributions

All authors contributed to the study conception and design. QW wrote the first draft of the manuscript. ZF conducted data collection and analysis and finalized the manuscript. XZ conducted material preparation and supervised the research process. All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

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Abbreviations

AIC: Akaike information criterion
BIC: Bayesian information criterion
CLM: conditional logit model
DCE: discrete choice experiment
ELM: Elaboration Likelihood Model
LL: log-likelihood
MXL: mixed logit model
PMT: Protection Motivation Theory
UTAUT: Unified Theory of Acceptance and Use of Technology

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