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A choice based conjoint analysis of mobile healthcare application preferences among physicians, patients, and individuals

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Junbok Lee [1], Jung Hyun Kim [2], Mingee Choi[3] & Jaeyong Shin [3,4] ✉

The rapid proliferation of healthcare service applications (apps) makes it challenging for consumers to determine the best one for their needs, prompting the Korean government to introduce an accreditation program to verify app safety. This study aims to identify the factors influencing the choice of healthcare service apps among physicians, patients with chronic diseases, and healthy individuals. We conducted a choice-based conjoint analysis with six factors (number of studies on effectiveness, frequency of information delivery, cybersecurity and data safety, user satisfaction, accreditation, and costs). 1,093 participants (407 healthy individuals, 589 patients, and 97 physicians) participated in the online survey. Across all groups, cybersecurity and data safety were the most important preference factors (healthy individuals: $\beta = 2.127$, 95% CI 2.096–2.338, patients: $\beta = 1.569$, 95% CI 1.481–1.658, physicians: $\beta = 1.111$, 95% CI 0.908–1.314). All groups were willing to pay more approximately \$12 for high cybersecurity and data safety compared to low.

With smartphone technology developing rapidly, many healthcare service applications (apps) have penetrated the market[1–4]. By using these healthcare apps, people are expected to be able to manage diseases better and achieve their health goals[5–8]. According to IQVIA's Digital Health Trends 2021 report, more than 90,000 healthcare apps were launched globally in 2020, bringing the total number to over 350,000[9]. Key categories include mental health and behavioral disorders (22%), diabetes (15%), heart and circulatory system (10%), digestive system (8%), and respiratory system (7%). However, despite the increased availability, 83% of the apps were installed fewer than 5000 times[9].

The presence and availability of multiple healthcare apps results in people having to seek clarification regarding which ones they should use. Psychological research suggests that people cannot make appropriate decisions when a large amount of information or options are available[10–12]. Similarly, in the healthcare market, people may find it challenging to determine which service is appropriate for a flood of services[13–15]. Several initiatives, such as the National Health Service app library in the UK and the Health Navigator app library in New Zealand, have attempted to address this problem[16,17]. The Korean government also launched an accreditation program to certify healthcare apps in 2022 to ensure people's safety by

addressing potential risks such as the misuse of healthcare information, provision of inaccurate information, hacking, and privacy breaches. This program has certified twelve healthcare service apps, and the accreditation is expected to be expanded.

For the meaningful use of the accreditation program, verifying the factors people consider when choosing a healthcare service app is essential[18–21]. Previous studies have explored these factors in different contexts. For instance, a conjoint analysis conducted in Germany focused on identifying the factors affecting their use of mental health apps[22]. Similarly, a study in the UK used conjoint analysis to confirm the factors healthcare professionals consider when choosing digital healthcare services[23]. While gathering opinions from a wide range of stakeholders for effective policy-making is essential, these studies are limited by only surveying healthcare professionals or the public.

This study aims to identify the preferences of physicians, patients with chronic disease, and healthy individuals when selecting healthcare service apps. Previous studies have shown that patients have 'experiential knowledge' gained through personal experiences related to their illness and symptoms, while physicians possess 'professional knowledge' based on theoretical and scientific understanding[24,25]. Healthy individuals lack both

[1]Institute for Innovation in Digital Healthcare, Yonsei University, Seoul, Republic of Korea. [2]Division of Tourism and Wellness, Hankuk University of Foreign Studies, Yongin, Korea. [3]Department of Preventive Medicine and Public Health, Yonsei University College of Medicine, Seoul, Republic of Korea. [4]Institute of Health Services Research, Yonsei University College of Medicine, Seoul, Korea. ✉e-mail: drshin@yuhs.ac

experiential knowledge and professional expertise. We hypothesize that these differences in knowledge may influence their app preferences. Specifically, physicians with professional knowledge will prioritize the validation of healthcare services effectiveness, chronic patients with experiential knowledge will place importance on user satisfaction, and healthy individuals with limited information will rely on accreditation. Based on the findings of this study, we propose policy implications for the accreditation program to enable more effective performance of healthcare apps.

Results

Characteristics of participants

Overall, as shown in Tables 1, 1093 people participated in the study: healthy individuals ($n = 407$), patients with chronic disease ($n = 589$), and physicians ($n = 97$). For healthy individuals, the number of participants was evenly distributed, as they were allocated proportionally by age and sex. Most patients with chronic disease were in their 40 s (26.8%) and 50 s (31.6%), while most physicians were in their 20 s (34%) and 30 s (62.9%). Both patients with chronic disease and physicians were predominantly male (72% and 93.8%, respectively).

Among the group of patients with chronic disease, the duration of illness was less than five years for 338 patients (57.4%), between five and ten years for 113 patients (22.6%), and more than ten years for 133 patients

(22.6%). 419 patients (71.1%) were taking medication, and 389 patients (66.0%) had a family history of hypertension or diabetes. 141 patients (23.9%) experienced complications, including cardiovascular disease ($n = 82$), cerebrovascular disease ($n = 30$), neuropathy ($n = 23$), nephropathy ($n = 22$), and others ($n = 30$).

Preference for healthcare service app

The preference for healthcare service apps across all groups is summarized in Table 2. Among healthy individuals, cybersecurity and data safety were considered the most important factors when choosing healthcare service apps ($\beta = 2.217$, 95% CI 2.066 to 2.338). The number of studies on effectiveness was also regarded as an important factor ($\beta = 1.678$, 95% CI 1.546–1.811). User satisfaction notably influenced app choice ($\beta = 1.118$, 95% CI 1.008 to 1.227). In addition, accreditation was found to have a meaningful influence ($\beta = 0.788$, 95% CI 0.700 to 0.875). However, they did not prefer providing excessive health information ($\beta = -0.295$, 95% CI -0.410 to 0.181).

For patients with chronic disease, cybersecurity and data safety were also the most important factors when choosing healthcare service apps ($\beta = 1.569$, 95% CI 1.481 to 1.658). The number of studies on effectiveness was the second most influential factor in their decision-making ($\beta = 1.383$, 95% CI 1.282 to 1.484). User satisfaction was also regarded as important ($\beta = 0.866$, 95% CI 0.782 to 0.951). In addition, accreditation contributed to app selection ($\beta = 0.717$, 95% CI 0.650 to 0.785). However, they did not prefer providing excessive health information ($\beta = -0.216$, 95% CI -0.303 to 0.130).

Among physicians, cybersecurity and data safety were considered the most critical factors ($\beta = 1.111$, 95% CI 0.908 to 1.314). The number of studies on effectiveness was also highly valued ($\beta = 1.083$, 95% CI 0.851–1.315). User satisfaction played an important role in app selection ($\beta = 0.865$, 95% CI 0.669–1.062). In addition, accreditation was noted as a contributing factor ($\beta = 0.504$, 95% CI 0.345–0.662). Physicians also did not prefer the provision of excessive health information ($\beta = -0.098$, 95% CI -0.295–0.100).

WTP for Healthcare Service App

We confirmed the relative preferences based on willingness to pay (WTP) (Table 3, Fig. 1). Healthy individuals were willing to pay more $13.36 (calculated as 2.217 for $\beta_{cybersecurity\ and\ data\ safety}$ divided by -0.166 for β_{cost}), for high cybersecurity and data safety compared to low. They were also willing to pay more $10.11 for three articles of proven effectiveness compared to none, $6.73 for high user satisfaction compared to low (under 80 s), and $4.75 for an accreditation. Patients with chronic disease were willing to pay more $12.35 for high cybersecurity and data safety, $10.89 for three articles of effectiveness, $6.73 for high user satisfaction, and $5.65 for accreditation. Physicians were willing to pay more $12.92 for high cybersecurity and data safety, $12.59 for three articles of effectiveness, and $10.06 for high user satisfaction, $5.86 for accreditation.

Discussion

This study attempted to confirm the preferences of patients with chronic disease, healthy individuals, and physicians when choosing healthcare service apps. The findings demonstrated that cybersecurity and data safety were the most critical attributes for all participant groups, followed by accreditation and studies published on effectiveness. All groups were willing to pay approximately $12 more for high cybersecurity and data safety and about $5 for accreditation. Compared to other groups, physicians were willing to pay more for services backed by published studies on effectiveness ($12.59) and those with high user satisfaction ($10.06).

This study's results suggest that the policy's effectiveness can be reinforced by providing more validation of cybersecurity or data safety, which was the highest preference factor across all groups. People take cybersecurity and data safety very seriously because healthcare data is sensitive to personal information that must not be compromised. A survey conducted on the purchase of mobile healthcare apps found that the public considered

Table 1 | Characteristics of Participants

Characteristics	Healthy Individuals	Patients with Chronic	Physicians
All	407 (100.0)	589 (100.0)	97 (100.0)
Age			
20 s	63 (15.5)	38 (6.5)	33 (34.0)
30 s	71 (17.4)	87 (14.8)	61 (62.9)
40 s	83 (20.4)	158 (26.8)	3 (3.1)
50 s	79 (19.4)	186 (31.6)	0 (0.0
60 s or above	111 (27.3)	120 (20.4)	0 (0.0
Gender			
Men	211 (51.8)	424 (72.0)	91 (93.8)
Women	196 (48.2)	165 (28.0)	6 (6.2)
Duration of illness			
Less than 5 years	–	338 (57.4)	–
5 to 9 years	–	118 (20.0)	–
10 years or more	–	133 (22.6)	–
Medication			
Yes		419 (71.1)	
No		170 (28.9)	
Family History			
Yes	–	389 (66.0)	–
No	–	200 (34.0)	–
Complication			
Yes*	–	141 (23.9)	–
Cardiovascular diseases	–	82 (-)	–
Cerebrovascular diseases		30 (-)	
Neuropathy	–	23 (-)	–
Nephropathy	–	22 (-)	–
Others	–	30 (-)	–
No	–	448 (76.1)	–

*Multiple selections allowed.

Table 2 | Preferences and WTP for healthcare service app

Attribute	Preference (β, 95% CI)			WTP* ($, 95% CI)		
	Healthy individuals	Patients	Physicians	Healthy individuals	Patients	Physicians
The number of studies on effectiveness (Reference: Zero)						
One	1.129*** (1.009 to 1.249)	0.985*** (0.891 to 1.079)	0.574*** (0.339 to 0.810)	6.80*** (6.08 to 7.52)	7.76*** (7.02 to 8.50)	6.67*** (3.94 to 9.42)
Two	1.351*** (1.222 to 1.480)	1.072* (0.971 to 1.173)	0.851*** (0.628 to 1.073)	8.14*** (7.36 to 8.92)	8.44* (7.65 to 9.24)	9.90*** (7.30 to 12.48)
Three	1.678*** (1.546 to 1.811)	1.383*** (1.282 to 1.484)	1.083*** (0.851 to 1.315)	10.11*** (9.31 to 10.91)	10.89*** (10.09 to 11.69)	12.59*** (9.90 to 15.29)
Frequency of information delivery (Reference: Two)						
Four	0.031 (-0.074 to 0.136)	−0.079 (-0.162 to 0.004)	−0.221* (−0.416 to −0.026)	0.19 (−0.45 to 0.82)	−0.62 (−1.28 to 0.03)	−2.57* (-4.84 to −0.30)
Six	−0.295*** (−0.410 to -0.181)	−0.216*** (−0.303 to −0.130)	−0.098 (−0.295 to 0.100)	−1.78*** (−2.47 to -1.09)	−1.70*** (−2.39 to -1.02)	−1.14 (−3.43 to 1.16)
Cybersecurity and data safety (Reference: Low)						
Medium	1.385*** (1.273 to 1.496)	1.037*** (0.952 to 1.121)	0.843*** (0.648 to 1.039)	8.34*** (7.67 to 9.01)	8.17*** (7.50 to 8.83)	9.80*** (7.53 to 12.08)
High	2.217*** (2.096 to 2.338)	1.569*** (1.481 to 1.658)	1.111*** (0.908 to 1.314)	13.36*** (12.63 to 14.08)	12.35*** (11.66 to 13.06)	12.92*** (10.56 to 15.28)
User satisfaction (Reference: Under 80)						
80-89	0.847*** (0.734 to 0.960)	0.582*** (0.496 to 0.668)	0.682*** (0.482 to 0.882)	5.10*** (4.42 to 5.78)	4.58*** (3.91 to 5.26)	7.93*** (5.60 to 10.26)
90 or above	1.118*** (1.008 to 1.227)	0.866*** (0.782 to 0.951)	0.865*** (0.669 to 1.062)	6.73*** (6.07 to 7.39)	6.82*** (6.16 to 7.49)	10.06*** (7.78 to 12.35)
Accreditation (Reference: No)						
Yes	0.788*** (0.700 to 0.875)	0.717*** (0.650 to 0.785)	0.504*** (0.345 to 0.662)	4.75*** (4.22 to 5.27)	5.65*** (5.12 to 6.18)	5.86*** (4.01 to 7.70)
Cost	−0.166*** (−0.176 to −0.157)	−0.127*** (−0.134 to −0.120)	−0.086*** (−0.101 to −0.071)	–	–	–

*p < 0.05, **p < 0.001.
†WTP, is calculated as β_i divided by β_{cost}, where β_i is a beta coefficient for attribute i, and β_{cost} is a beta coefficient for the cost attribute (WTP$_i$ = β_i / β_{cost}).

Table 3 | WTP for healthcare service app related to preference

Attribute	Gender		Age				
	Men	**Women**	**20 s**	**30 s**	**40 s**	**50 s**	**60 s or above**
The number of studies on effectiveness (Reference: Zero)							
One	6.91 (6.26 to 7.55)	8.08 (7.20 to 8.97)	10.20 (8.49 to 11.91)	8.78 (7.26 to 10.28)	5.93 (4.88 to 6.98)	7.55 (6.51 to 8.60)	7.42 (6.33 to 8.50)
Two	7.80 (7.11 to 8.49)	9.25 (8.30 to 10.20)	9.30 (7.49 to 11.11)	9.15 (7.54 to 10.77)	7.74 (6.61 to 8.87)	9.00 (7.89 to 10.11)	8.41 (7.25 to 9.57)
Three	9.94 (9.25 to 10.63)	11.62 (10.64 to 12.60)	11.66 (9.81 to 13.52)	11.66 (10.03 to 13.28)	9.75 (8.62 to 10.88)	11.66 (10.52 to 12.80)	10.34 (9.18 to 11.51)
Frequency of information delivery (Reference: Two)							
Four	−0.49 (−1.06 to 0.08)	0.17 (−0.61 to 0.95)	0.39 (−1.07 to 1.86)	0.21 (−1.12 to 1.53)	−0.62 (−1.55 to 0.31)	−0.26 (−1.18 to 0.65)	−0.52 (−1.48 to 0.45)
Six	−1.40 (−1.99 to −0.80)	−2.32 (−3.15 to −1.48)	−0.39 (−1.96 to 1.16)	−0.94 (−2.32 to 0.45)	−1.38 (−2.35 to −0.40)	−2.49 (−3.48 to −1.51)	−2.54 (−3.55 to −1.52)
Cybersecurity and data safety							
Medium	7.65 (7.07 to 8.23)	9.30 (8.48 to 10.11)	8.91 (7.41 to 10.41)	9.29 (7.94 to 10.64)	7.43 (6.48 to 8.38)	9.33 (8.37 to 10.30)	8.04 (7.05 to 9.02)
High	11.54 (10.93 to 12.15)	15.07 (14.18 to 15.96)	15.22 (13.56 to 16.88)	14.53 (13.09 to 15.96)	11.03 (10.04 to 12.02)	14.41 (13.38 to 15.44)	12.40 (11.37 to 13.45)
User satisfaction							
80-89	4.40 (3.81 to 4.99)	5.49 (4.65 to 6.31)	6.82 (5.26 to 8.37)	5.64 (4.26 to 7.02)	3.78 (2.82 to 4.74)	5.45 (4.48 to 6.43)	4.30 (3.30 to 5.29)
90 or above	6.48 (5.89 to 7.06)	7.25 (6.44 to 8.05)	8.68 (7.14 to 10.21)	7.79 (6.44 to 9.15)	6.40 (5.45 to 7.34)	7.44 (6.50 to 8.39)	5.74 (4.77 to 6.72)
Accreditation							
Yes	5.00 (4.54 to 5.46)	5.70 (5.05 to 6.34)	5.32 (4.10 to 6.54)	5.29 (4.21 to 6.37)	5.05 (4.29 to 5.81)	5.12 (4.37 to 5.88)	6.21 (5.43 to 6.99)

(USD; WTP (95% CI)).
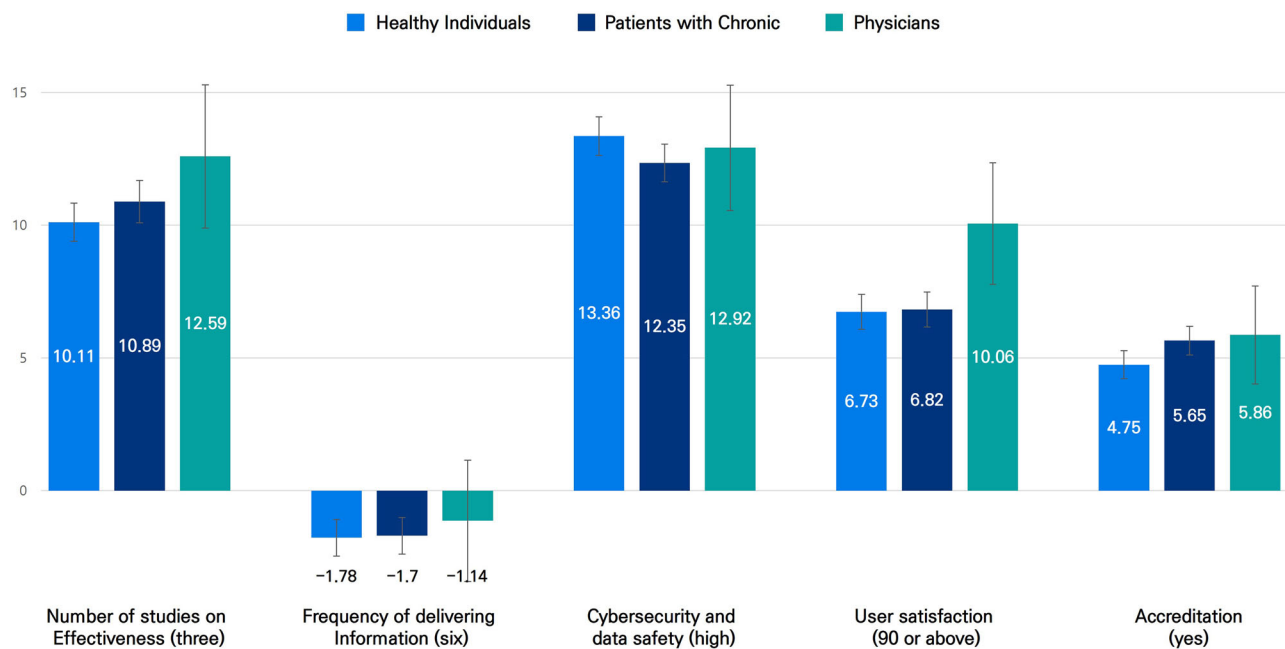
Fig. 1 | WTP for healthcare service app related to preferences. Preferences for key attributes of digital health services were evaluated by calculating the WTP for each feature. WTP was determined by dividing each attribute's beta coefficient by the cost attribute's beta coefficient ($\text{WTP}_i = \beta_i / \beta_{\text{cost}}$). This calculation estimated how much each group would pay for specific attributes. Healthy individuals, patients with chronic diseases, and physicians were willing to pay more for cybersecurity and data safety: $13.36, $12.35, and $12.92, respectively. They were willing to pay $4.75, $5.65, and $5.86 for accreditation, respectively. Physicians showed a higher willingness to pay for each study on effectiveness ($12.59) compared to healthy individuals ($10.89) and patients with chronic disease ($10.89). Similarly, physicians were willing to pay more for user satisfaction ($10.06) than healthy individuals ($6.73) and patients with chronic disease ($6.82). All groups were negatively willing to pay for information delivery.

security and privacy the second most important factors[26]. Information security was the most important factor in a study examining physicians' preferences for mHealth services[27]. Other previous studies have also reported that data security is one factor that increases people's WTP for digital health[28,29]. In addition, various preference studies have recognized cybersecurity and data safety as crucial factors in relation to digital healthcare products and information[30–33]. In South Korea, a survey conducted by a government agency found that improving digital healthcare requires ensuring the reliability and accuracy of data, protecting personal information, and establishing a robust security system. The results of our study further reinforce and support these previous research findings. The National Healthcare App Accreditation Program in Korea aims to ensure people's safety when using healthcare service apps. Given the study's findings, the accreditation program's goals are well-aligned with people's needs.

The results of this study also confirm the importance of government accreditation. All three groups showed significant results regarding WTP for mobile healthcare apps with official accreditation. The result means that, given the ever-increasing number of mobile healthcare apps, individuals may struggle to decide which apps to trust, and government certification can serve as a valuable guide in their decision-making process. These findings align with a discrete choice experiment conducted in the United Kingdom, which revealed that physicians prefer mobile health services approved by the National Health Service[23]. In addition, conjoint analysis or discrete choice experiment studies that found people prefer government-developed digital health products or government-managed digital health data can be understood in the same context as our results[30,34–36].

We identified differences in the relative importance and WTP for each attribute according to demographic characteristics. Our study found that patients with chronic disease tended to be willing to pay more for healthcare service apps with accreditation compared to healthy individuals. It is presumed that the government certification ensures verified service quality and safety, which likely contributes to the higher WTP among patients with chronic disease than healthy individuals. While not directly focused on accreditation, previous studies highlighting higher WTP among chronic disease patients may reflect similar underlying reasons[37,38].

Women were willing to pay more than men for apps with solid cybersecurity and data safety features. This finding is consistent with previous studies showing that women tend to be more cautious in their cybersecurity practices than men[39,40]. However, in a study conducted in Hong Kong with the public, men showed a stronger preference for products with high security and privacy features than women[26]. This difference from previous studies could be attributed to the fact that this study's descriptions additionally included information about potential failures and technical defects. However, further research is needed to understand these findings fully.

Individuals in their 60 s and older had the highest willingness to pay for apps with accreditation. It may be because older people tend to trust accreditation more due to their relatively low digital literacy and lack of information about digital healthcare services[41,42]. Younger people were relatively willing to pay more for apps with solid cybersecurity and data safety and high user satisfaction than other age groups. Younger people regarded privacy as a more critical consideration in a study investigating preferences for mHealth technologies for managing depression[33]. Growing up with digital devices from an early age, they conduct many of their activities online, making them likely to be more concerned about cybersecurity and data safety[43]. Additionally, since they often rely on other users' ratings and reviews when purchasing products online, user satisfaction with healthcare service apps may play an essential role in their decision-making. Considering this relative importance and WTP, the attributes of healthcare services should be emphasized differently depending on the age of the target consumer[44,45].

Consistent with previous research, physicians preferred mobile healthcare apps that demonstrated clinical effectiveness, aligning with findings from earlier studies conducted among physicians in the UK[23]. In a study examining the preferences of German medical students regarding

digital mental health interventions, the scientific evidence base was identified as a significant factor influencing their choices[46]. Respiratory specialists, Dutch dermatologists, Norwegian general practitioners, and Belgian family doctors also require strong evidence before incorporating adaptive digital health technology into clinical practices[47–51]. For a healthcare service app to be used effectively, it is necessary to first persuade medical professionals by confirming its effectiveness before they recommend it to their patients.

In this study, the frequency of delivering information was insignificant, whereas certain other factors were significant for people's preferences. It can be interpreted as users prefer to provide only a little information. Therefore, efforts should be made to provide users with customized rather than excessive information.

This study is meaningful in confirming the preference for healthcare service apps among various groups, such as medical professionals, patients with chronic diseases, and healthy individuals. However, this study has several limitations. First, there may be inherent limitations since our research was based on an online survey. This method may yield different results compared to purchasing situations in a real-world setting. Specifically, we only presented two options in our survey, whereas, in reality, consumers typically compare a wider range of services before deciding. Additionally, because the survey was conducted online, we could not verify whether participants had a medical condition. Second, there are also limitations related to the attributes and levels. People may consider other attributes more critical than those included in this study. It was also challenging to ensure that they fully understood these aspects due to the nature of an online survey, even though we continuously displayed explanations of the attributes and levels and provided 15 seconds for participants to consider them. To address this limitation, including a quiz to confirm their understanding after reading the explanation on attributes and levels would be helpful. It is necessary to help participants understand through sufficient explanation of each attribute and level[52]. Additionally, we did not provide visuals to assist them, which would have been helpful but was not implemented. Third, patients with chronic disease include only those with high blood pressure and diabetes, whereas others may have different preferences. Regarding the healthy individual group, it is also possible that we did not screen accurately, as we only asked whether they had received a chronic disease-related diagnosis, using hypertension and diabetes as examples. Fourth, the smaller sample size of the physician group ($n = 97$) may limit this study's generalizability and comparison robustness. The survey also may not fully represent all South Korean physicians, as it primarily consisted of younger physicians, and not all age groups were included. These factors should be considered when interpreting the results.

In conclusion, digital healthcare technology will continue to evolve, and more healthcare service apps are expected to be developed. For the effective use of these services, users' preferences must be checked. Governments that manage and authorize these services also need to implement policies based on users' and providers' needs.

Methods
Study design
We conducted a choice-based conjoint analysis (CBCA), a method for preference elicitation that uses a survey instrument to force participants to trade-off between attributes, allowing their underlying preferences to be estimated through statistical analysis[53–55]. The basic principle of CBCA is that the profiles that constitute a choice set share the same attributes but are differentiated by the attributes' levels, which are controlled experimentally. Participants make choices in a series of choice sets, and the pattern of responses allows us to quantify the impact of changes in attribute levels on choice[56]. There are several types of CBCA, with the two main ones being traditional CBCA, which presents a fixed choice task with a set combination of different product attributes, and Adaptive Choice-Based Conjoint (ACBC), in which the tasks are adjusted based on the respondent's preferred attributes identified from the initial choice[57,58]. In this study, we adopted the traditional CBCA approach of presenting fixed-choice tasks. The methodological framework of this study (including instrument, design,

Table 4 | Description of Attributes and levels

Attribute	Level	Description
The number of studies on effectiveness	0, 1, 2 or 3	Researching to objectively verify whether healthcare services have effectively improved users' health and submitting articles on the results to an academic journal through expert review.
Frequency of information delivery	Twice, Four times, Six times / month	Providing healthcare education materials such as card news, leaflets, and videos online so that healthcare service users can change their health awareness, knowledge, and behavior.
Cybersecurity and data safety	Low, Mid, High	Ensuring personal information protection and data security systems when providing online healthcare services by coping with possible failures and technical defects.
User satisfaction	Under 80, Between 80–89, Above 90	The degree to which healthcare service users are satisfied with the service subjectively.
Accreditation	Yes or no	A program that the Korean Ministry of Health and Welfare gives accreditation for services that provide counseling, education, training, and practical programs for promoting health and preventing diseases.
Cost	0, $5, $10, $15/month	The service cost that will be paid for a month to use mobile healthcare services.

deployment, and data analysis) was consistent with ISPOR—the Professional Society for Health Economics and Outcomes Research Good Research Practice for Conjoint Analysis[59].

Development of attributes and levels

The attributes and levels in this study were designed based on the evaluation criteria of the 'National Healthcare App Accreditation Program in Korea.' The accreditation program divides the types of certifications into three categories (chronic disease management, lifestyle modification management, and simple information delivery) according to the characteristics of mobile applications (see Supplementary Table 2). According to previous research, where many studies have used six attributes, we have also set the number of attributes in our study to six[60]. There are a total of 14 indicators in the accreditation program; we selected four indicators that are evaluated in all three certification types: (1) the number of studies on effectiveness, (2) frequency of information delivery, (3) cybersecurity and data safety, (4) user satisfaction. We also included two additional variables, 'accreditation' and 'cost', resulting in six attributes (see Table 4). To determine the levels for the selected attributes, we either directly adopted the indicators from the accreditation program or referred to the levels utilized in previous studies[22,23,26,61,62].

The number of studies on effectiveness. This attribute was divided into levels of 0, 1, 2, and 3. In previous studies, the 'number of studies concerning safety and effectiveness' levels were set at '0, 1, 2, 3, ' while the levels for 'proven effectiveness' were set as 'yes, not yet'[22,23]. In our study, we opted for polytomous levels instead of binary levels to derive more meaningful analyses.

Frequency of information delivery. The levels for the frequency of information delivery were set at 2, 4, and 6 times per month. Due to the lack of prior research on this attribute, these levels were aligned with the evaluation criteria of the Korean accreditation program.

Cybersecurity and data safety. We categorized cybersecurity and data safety into three levels - low, medium, and high - due to the difficulty of assigning a precise numerical score to this attribute. Similarly, previous research has classified the attributes of 'security and privacy' into three levels: no security assurance, some assurance, and complete security assurance[26].

User satisfaction. User satisfaction is categorized into under 80, between 80–89, and above 90. In previous studies, attributes such as 'the app has been recommended by other healthcare professionals' or 'the ratings of the app' were used, with levels defined as 'yes or no' or '3.2, 4.0, 4.8 (out of 5), ' respectively[23,26]. We maintained three levels but a more intuitive and familiar scale to obtain more insightful data, dividing scores in 10 out of 100 increments.

Accreditation. Following previous research, the accreditation level was set as binary, with 'yes' or 'no' options[23].

Cost. Our previous research found that WTP for mobile health services in South Korea ranged from $9.3 to $16.0, depending on service experience and type[37]. Based on these findings, we categorized the cost levels into multiples of 5, with a minimum value of 0 and a maximum value of 15.

We utilized the software provided by Sawtooth (Utah, USA) to design our CBCA, generating 15 paired questions to present the attributes and levels of the service. Sawtooth is widely recognized in the field of conjoint analysis, allowing us to efficiently model and measure respondents' trade-offs between different service attributes[63]. According to previous research, the choices typically used include binary options, where respondents choose between two alternatives, or ternary options, where three alternatives are provided[64]. Following prior studies, by presenting two pairs of choice, we could manage the cognitive load on respondents while still gathering robust data[22,23,26,65].

Participants

An online/mobile survey targeting healthy individuals aged 20 years or older ($n = 407$), patients with hypertension or diabetes ($n = 589$), and physicians ($n = 97$) was conducted. The inclusion criteria for this study were as follows: (1) adults aged 19 years or older; (2) individuals without any diagnosed chronic disease, patients diagnosed with hypertension or diabetes, and physicians with a medical license number; and (3) no difficulty in completing the online questionnaire. Exclusion criteria are (1) those who did not consent to the study and (2) those who lacked the decision-making capacity to complete the online survey.

For healthy individuals and patients with hypertension or diabetes, e-mails were sent to online panel members registered with Gallup Korea (Seoul, Korea) to provide information on the survey outline and to participate if desired. For the healthy individual group, we asked whether they had ever been diagnosed with a chronic disease, using hypertension and diabetes as examples. We only included those who reported no diagnosis. In the case of the patient group, we asked whether they had been diagnosed with hypertension (ICD-10: I10–I15) or diabetes (ICD-10: E10–E14), and those who responded that they had been diagnosed were included in the patient group. Healthy individuals were recruited through proportional allocation based on sex, age, and region in Korea as of 2022. Patients with hypertension or diabetes participated in the survey on a first-come, first-served basis because it was difficult to determine the parameters for proportional allocation.
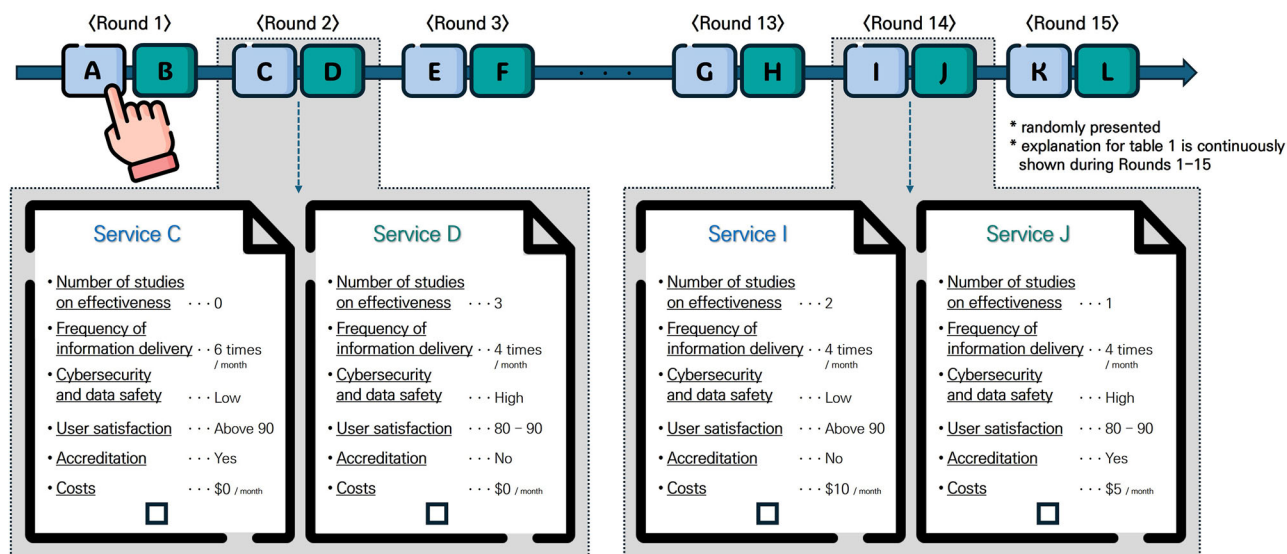
Fig. 2 | The flow of choice tasks and examples of options. In this survey, participants selected one of two service options with differing attributes across 15 separate questions. They had to choose between the two options without the ability to skip or opt-out. A 15-second minimum time limit was enforced for each question to encourage thoughtful consideration of the choices. Descriptions of the attributes were persistently displayed at the top of the page for clarity. The order of the questions was randomized to mitigate the risk of bias from the sequence of questions.

The physician participants were recruited through an announcement posted on a physician community website with approximately 23,000 registered physicians. The website verifies the license numbers of its members to ensure they are practicing physicians. The website allows physicians to chat, use anonymous message boards, provide lecture content, and post job listings. It also offers a service for surveying physicians, which we used to recruit participants and conduct the survey.

Healthy individuals and patients who participated in the survey received $2.50 (1 USD = 1200 KRW) as incentives, and doctors received $16.67. A survey of healthy individuals and patients with chronic disease was conducted between January 16 and February 2, 2023, and a survey of physicians was conducted between August 10 and 14, 2023. No follow-up reminders were sent to participants.

Online survey procedure
The participants first responded to questions about their demographic characteristics (sex, age, and place of residence). Only the patients then answered additional questions regarding the duration of their illness, medication, family history of hypertension or diabetes, and complications. Healthy individuals and physicians did not answer these questions and proceeded directly to the next step. Next, they read an explanation of mobile-based healthcare services. This service assists individuals in managing their health by using personal data entered through a smartphone, such as steps, weight, and meal records. Based on this data, the service creates personalized exercise and diet plans. It also provides support through regular messages that offer tailored counseling, education, and advice, helping users keep healthy habits and make informed health decisions.

Subsequently, the participants were asked to choose their preferred service from the two paired services, each presenting different levels of a given attribute, as shown in the example in Fig. 2. They completed a total of 15 such questions. To maximize the information collected and reduce interpretation bias, we did not provide an opt-out option and required participants to select one of the two service options. We also enforced a rule requiring participants to spend a minimum of 15 seconds on each question, ensuring they had sufficient time to consider the attributes and levels. The required time was set in consultation with Gallup Korea's members, recognizing that it is easy for participants to respond quickly without providing adequate consideration in online research. In addition, an explanatory text, as presented in Table 4, was provided to help participants to understand the factors accurately. It was continuously presented at the top of the survey page so they could view it while answering the survey. In addition, to help participants identify the differences in levels for each attribute, we used different font colors to highlight the differences between the two choices. The questionnaire items were randomly rotated and presented to reduce order bias. Gallup Korea developed the survey pages.

Statistical analysis
For this study, we analyzed participant preferences using a conditional logit model implemented in STATA version 16. We coded all attributes as categorical variables, except for cost, which was treated as continuous to identify trade-offs in WTP for attributes of the healthcare service app[23]. We estimated a main effect model for each group. A WTP analysis was also conducted to understand how participants are willing to trade one attribute for another. It is crucial in this study because differences in preferences cannot be compared solely based on beta coefficients from a main effects analysis, given that the study involves three different populations. As shown in Eq. (1), the WTP for each attribute was calculated by dividing attribute's beta coefficient by the cost attribute's beta coefficient, enabling us to estimate the WTP for specific attributes[23].

$$\text{WTP}i = \beta i \div \beta \text{cost} \qquad (1)$$

- WTP$_i$ represents the willingness to pay for attribute i.
- β_i is a beta coefficient for attribute i.
- β_{cost} is a beta coefficient for the cost attribute.

We further divided into subgroups based on age and gender and calculated each group's WTP. This analysis reveals how much each subgroup will pay for a particular attribute.

Ethics approval
All procedures were conducted according to ethical standards and the principles outlined in the Declaration of Helsinki. This study was approved by the Institutional Review Board of Yonsei University (4-2022-1517). After reading the explanation page, which included information about the study's goals, participants, and data storage time, all participants consented. There was no preregistration for this study.

Data availability

The data gathered and examined in this research can be accessed only through the corresponding author, provided that the request is justified and approved by the institutional review board.

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Author contributions
Concept and design: J.B.L. and J.H.K. Acquisition, analysis, or interpretation of data: J.B.L., J.H.K., M.G.C, and J.Y.S. Drafting of the manuscript: J.B.L. Critical revision of the manuscript for important intellectual content: J.B.L., J.H.K., and J.Y.S. Administrative, technical, or material support: J.Y.S. Supervision: J.Y.S. All authors read and approved of the final manuscript.

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Correspondence and requests for materials should be addressed to Jaeyong Shin.

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