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Towards an Integrated Online–Offline Healthcare System: Exploring Chinese Patients’ Preferences for Outpatient Follow-Up Visits Using a Discrete Choice Experiment

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Abstract: Public hospitals in China are working to build an integrated online–offline healthcare system that combines telehealth and traditional healthcare to better serve patients. This study aims to explore Chinese patients’ preferences for online versus offline outpatient follow-up visits after the COVID-19 pandemic and to inform healthcare providers in designing optimal service delivery programmes. A discrete choice experiment was designed to elicit respondents’ stated preferences. A total of 311 valid respondents were recruited. Analysis of the full sample showed that respondents preferred traditional, offline outpatient follow-up visits. Nevertheless, a class of respondents was identified who preferred online outpatient follow-up visits. Our results show that Chinese patients are currently generally cautious about online outpatient follow-up visits since there is proportion of potentially targeted patients who stated a preference for online visits while the overall preference is still offline, in-person follow-up visits. Online outpatient follow-up visits could be attractive alternatives to traditional visits if they could meet potential users’ preferences for shorter waiting time for appointments, lower service cost, and continuity of follow-up visits. This study also suggests that it is necessary and worthwhile for healthcare providers to further explore the optimal integration of telehealth services with traditional healthcare.



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Keywords: telehealth; Internet hospital; healthcare system; patient preference; willingness to pay; discrete choice experiment

1. Introduction

Global health systems face challenges related to public health emergencies, such as the COVID-19 pandemic, and there is an urgent need to reform health systems and innovate in service delivery. The integration of intelligent technology into healthcare to facilitate telehealth services has gained significant popularity in recent years [1]. Telehealth covers a broad range of health-related services delivered through information and communication technologies such as patient care, education, and remote monitoring [2]. Today, the use of telehealth is recognised as an innovation in digital healthcare with a promising application [3]. It has potential benefits in reducing hospital overcrowding, facilitating access to care, saving time and money, allowing access to health-related information, supporting chronic disease management, and assisting rural hospitals in providing specialist care [4,5]. In particular, the explosion of COVID-19 has accelerated the adoption and use of telehealth services, making telehealth an important tool for alternative face-to-face care during this period [5,6].

To meet the growing demand for healthcare services, the Chinese government is actively exploring the application of Internet information technology to provide telehealth services, aiming to establish an integrated online and offline medical service mode. Against this background, Internet hospitals have emerged and been vigorously promoted. The operation of Internet hospitals is based on offline physical healthcare institutions [7], which

use the healthcare resources of physical hospitals and Internet technology to provide online and offline closed-loop healthcare services [8], including online outpatient follow-up consultation services for patients with common and chronic diseases, and services such as online appointment scheduling, electronic medical records, online payment, and medication delivery that do not involve diagnosis and treatment. At present, the large number of public Internet hospitals run by traditional public hospitals in China dominate the domestic market and are most used by Chinese patients compared to other types of Internet hospitals [9].

Internet hospitals have the advantage of overcoming the time and geographical barriers to traditional healthcare delivery. In China, large numbers of patients with common and chronic diseases often flock to tertiary hospitals, causing overcrowding and increasing the average waiting time for patients in hospitals. Long waiting time for appointments, long waiting time in hospitals, and short consultation time with doctors have caused dissatisfaction among many patients and led to a poor doctor–patient relationship. Moreover, patients residing in rural or remote areas face significant challenges, including long distances, high transportation expenses, and time constraints when seeking high-quality specialist consultations at large hospitals. Internet hospitals offer viable solutions to these problems. For hospitals, congestion in physical hospitals can be reduced by transferring a proportion of patients with common and chronic diseases who are suitable for remote, online outpatient follow-up to Internet hospitals. Routine follow-up patients and patients who are inconvenienced when visiting a hospital in person can benefit from the reasonable use of Internet hospitals, reducing the time and money spent on unnecessary travel to physical hospitals. Although Chinese patients' attitudes towards telehealth are generally positive, only a small proportion of them actually use it [10]. On the one hand, some patients know little about Internet hospitals. On the other hand, due to traditional medical beliefs, some patients believe that Internet hospitals are unreliable [7]. There is a growing demand for high-quality healthcare services, including telehealth services, among Chinese residents [11], especially for patients with chronic diseases, for whom Internet hospitals can serve as a bridge for long-term follow-up and chronic disease management [8]. However, little is currently known about the needs and preferences for online outpatient follow-up visits provided by public Internet hospitals in China.

Understanding the factors that influence consumer demand for healthcare is critical to the delivery of health services and the development of health policy [12]. The effectiveness of telehealth as an alternative to face-to-face visits depends on achieving high rates of uptake among the target population. It is therefore important to understand the factors that may increase the acceptability of telehealth. Patient-centred design and delivery of services that meet patients' preferences and needs are considered an important goal for health system improvement [13]. To date, there has been scant research on Chinese patients' preferences for remote follow-up. However, assessing patients' preferences for remote follow-up is the first step in designing effective patient-centred health services. Information on patients' preferences can be used to identify the gap between ideal and actual healthcare and thus optimise service delivery solutions. In addition, understanding the factors that matter most to patients can help healthcare practitioners prioritise the allocation of healthcare resources. Whether investigating the impact of health policies on individual well-being, estimating the value of new interventions to society, or explaining and predicting demand for healthcare, there is a need for information on individuals' preferences for health services or interventions [12].

There has been some initial exploration of studies that measure stakeholders' (patients, clinicians, policy makers, etc.) preference for telehealth solutions over traditional healthcare solutions. The methods commonly used to elicit preferences can be classified into direct methods, which involve ranking or rating the importance of a set of attributes, and indirect methods, which involve discrete choice experiments (DCEs) [14]. The discrete choice experiment (DCE) has become a commonly used, stated preference technique in health economics and health policy analysis because it allows not only to quantify the extent

to which respondents trade off different telehealth attributes, but also to estimate the willingness to pay (WTP) for a change in the level of the preferred attribute and to predict the probability of choosing a particular telehealth service alternative [15–17]. Studies that have used DCE to measure respondents' preferences for telehealth services versus traditional healthcare have typically found that cost, speed of access to care, including long-term waiting time (waiting for an available appointment) and short-term waiting time (waiting on the day of the appointment), quality of consultation, and continuity of care are important factors influencing the choice of healthcare services [13,18–23]. The majority of these studies found that patients preferred traditional healthcare, lower cost, shorter waiting time, and more familiar doctors.

Specifically, preferences for telehealth services versus traditional healthcare have been investigated in different healthcare scenarios, such as web-based exercise telerehabilitation [13], cardiac telemedicine (new diagnosis for heart problems) [18], primary care consultations (consultation with a family doctor, consultation for antibiotic treatment, etc.) [19–22], and initial COVID-19 diagnosis [23]. In the area of telerehabilitation, research has shown that chronic pain patients prefer face-to-face consultations with physicians to consultations that are fully or partly delivered via remote video communication [13]. Regarding telemedicine cardiology services, Deidda et al. [18] found that the majority of potential users in Italy preferred to visit hospitals and private systems rather than telemedicine through family doctors or pharmacies. In primary care, Buchanan et al. [19] investigated the UK public's preference for online consultation when they had symptoms that might be appropriate for antibiotics. The results showed that the UK public valued consultation with local medical centres over online providers, in addition to showing a preference for reputable clinicians. Studies by Chudner et al. [20] and von Weinrich et al. [21] found that respondents preferred in-clinic consultations to video consultations. Differently, in the study by Chudner et al. [20], Israeli patients most valued the quality of the consultation and did not expect to be interrupted during the consultation. Whereas in the study by von Weinrich et al. [21], German patients placed the highest value on the level of continuity of care. Mozes et al. [22] assessed the attributes on patient preferences for telemedicine versus in-clinic consultations during the COVID-19 pandemic, and their study identified four important attributes proposed by patients: time until the appointment, severity of the medical problem, patient–physician relationship, and flexible reception hours. Another study compared the preferences for initial fever diagnostic attributes of the Chinese and American public during the COVID-19 pandemic. Chinese respondents expressed a preference for visiting a fever clinic over online consultations, while American respondents preferred private clinics [23].

In comparison, several studies have reported respondents' preferences for telehealth or integrated services that combine telehealth with traditional healthcare in specific circumstances. For example, an initial survey by Qureshi et al. [24] found that dermatology patients preferred telemedicine and were willing to pay for expedited access to their doctors via telemedicine. Australian patients who had participated in outpatient telemedicine consultations expressed a preference for video consultations at the patient's local general practitioner practice or hospital, followed by video consultations at home, and finally travelling for an in-person appointment [25]. Both groups of respondents surveyed before and during the COVID-19 pandemic preferred a combined diagnosis by both AI and human clinicians over an AI-only diagnosis or a human-only diagnosis [26].

To the best of our knowledge, there are no studies that have applied DCE to investigate Chinese patients' preference for online outpatient follow-up visits versus traditional, offline, and in-person follow-up visits after the COVID-19 pandemic, and to assess the relative importance of different aspects of factors influencing patients' decision-making behaviour. Therefore, this study aims to assess whether Chinese patients prefer and are willing to pay for online outpatient follow-up visits via public Internet hospitals, and to explore the heterogeneity of patient preferences. Our results found that Chinese patients generally preferred traditional, offline, in-person follow-up visits to online outpatient follow-up visits,

but there was a group that expressed a preference for online outpatient follow-up visits that also had a strong preference for short appointment waiting time and low cost. This suggests that the operation of public Internet hospitals could be valuable for the sustainability of China's healthcare system in the foreseeable future. Telehealth services can be used as an alternative to traditional face-to-face healthcare in healthcare scenarios where the use of telehealth is appropriate, such as routine and regular follow-up visits for non-urgent chronic conditions.

There are three main contributions of this paper. First, it provides current Chinese patients' perceptions of telehealth services provided by Internet hospitals. Patients' attitudes and preferences have important practical implications for the future implementation of telehealth. Our study can provide empirical data to predict the uptake of telehealth. Secondly, the empirical findings of this paper provide ideas for health policy development. The study identified patients' sensitivities to cost, accessibility (waiting time), and quality (continuity) when choosing healthcare services; these patient-valued factors can be taken into account by policy makers when developing health policies to promote the adoption of telehealth. At the same time, patient preferences for telehealth need to be evaluated on an ongoing basis in order to provide personalised telehealth services that meet the needs of different patient groups. Thirdly, this paper informs the integration of telehealth into healthcare systems to promote 'patient-centred' healthcare design and delivery. Patient involvement in the design, delivery, and evaluation of telehealth services is key to the successful implementation of telehealth and there is a need to focus on improving the delivery of telehealth services around the priorities identified by patients and to use the strengths of telehealth to provide integrated care to patients. Given that traditional healthcare services in some cases do not meet patients' needs and that patients are cautious about the effectiveness of telehealth, it is valuable and necessary to combine the strengths of telehealth and traditional healthcare in practice to design and deliver integrated online and offline healthcare services.

2. Materials and Methods

2.1. DCE Methodology

Originally developed in marketing, transport, and environmental economics, DCE has become an increasingly popular stated preference method in healthcare [27,28]. Economists usually obtain information about consumer preferences by analysing market-based data, but market data are limited in the healthcare industry, so stated preference techniques are widely used in health economics [12]. Based on value theory and random utility theory [29–32], the approach assumes that healthcare interventions, services, or policies can be characterised by their attributes. Individuals' evaluations depend on the level of these attributes. Choices are based on potential utility functions, and stated preferences are revealed through choices. In DCE, respondents are presented with a series of choices and individuals are asked to choose the most preferred alternative among alternatives described by product or service attributes, where the attributes vary within a specified and reasonable range of levels [33,34]. In addition to assessing stakeholder preferences for health services, interventions, or treatment programme attributes, as well as measuring willingness to pay, DCE can also be used to predict the uptake and adoption of new interventions or services, which can provide valuable information for health policy development [12,30,35].

As shown in Figure 1, the first step is to define the research question, then select the attributes and levels, create the experimental design and construct the choice set. Next, a complete preference questionnaire was developed, and finally, data collection and data analysis were carried out.

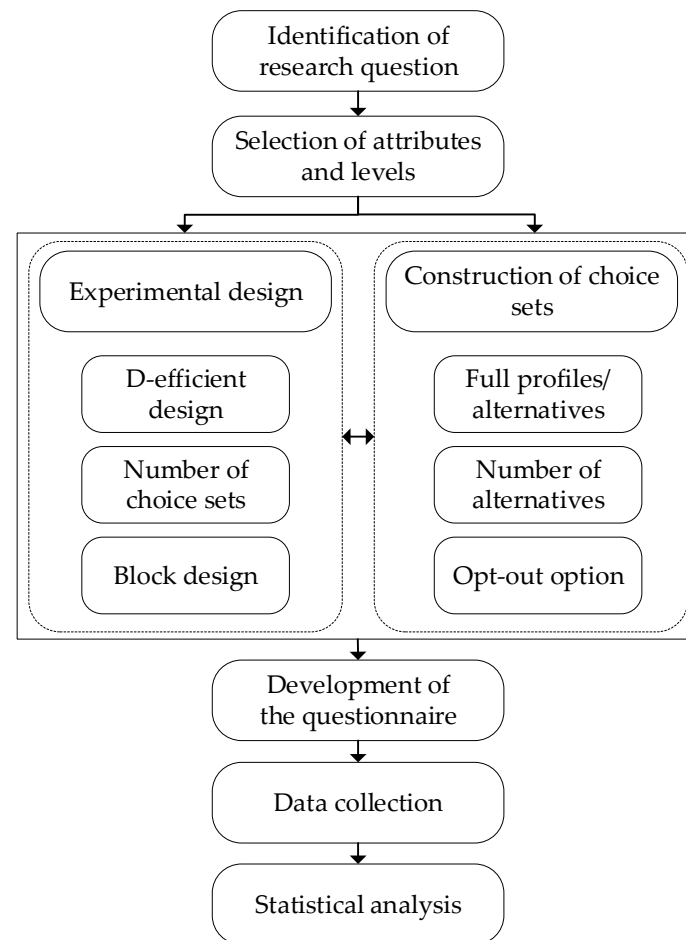


Figure 1. Research flow of discrete choice experiment.

2.2. Attributes and Levels

Following the Good Research Practices suggested by ISPOR (International Society for Pharmacoeconomics and Outcomes Research), consultation with experts, qualitative research, or other preliminary research can provide the basis for identifying and selecting attributes and attribute levels [15]. After a detailed review of the attributes included in relevant studies and an investigation of the practical operational data of Internet hospitals in China, the following six attributes were selected, and a reasonable range of levels was assigned to each attribute. As shown in Table 1: (1) Cost (Chinese Yuan, CNY): this refers to the cost of an online or offline outpatient follow-up visit. (2) Mode of follow-up visit: the follow-up mode includes two levels: traditional, offline, in-person follow-up visit and telehealth visit (online outpatient follow-up visit through the public Internet hospital). (3) Choice of follow-up doctor: this attribute indicates the continuity of the doctor–patient relationship, specifically whether the doctor is the doctor who first diagnosed the patient in the hospital where the patient was first diagnosed. (4) Waiting time for an appointment: this measures the number of days waiting for an available online or offline outpatient follow-up appointment. (5) Waiting time on appointment day: this attribute describes the waiting time before the consultation on the day of the follow-up visit. (6) Payment method: this refers to either payment with or without medical insurance.

Table 1. DCE attributes and attribute levels.

Attribute	Level	Level Name
Cost (CNY)	10 (reference)	Cost 10
	25	Cost 25
	50	Cost 50
Mode of follow-up consultation	Offline, in-person follow-up visit (reference)	Mode Offline
	Online outpatient follow-up visit	Mode Online
Choice of follow-up doctor	The patient's own initial diagnostician (reference)	Initial Doc
	Non-initial diagnostician at the hospital of initial diagnosis	NIDocIHos
	Non-initial diagnostician at the hospital of non-initial diagnosis	NIDocNIHos
Waiting time for an appointment	0 day/Today (reference)	0 Day
	3 days	3 Days
	7 days	7 Days
Waiting time on appointment day	10 min (reference)	10 Min
	30 min	30 Min
	60 min	60 Min
Payment method	Payment with medical insurance (reference)	With MI
	Payment without medical insurance	Without MI

2.3. DCE Design

DCE design needs to consider whether alternatives include labels, full factorial or fractional factorial designs, orthogonal or efficient designs, whether attribute interactions need to be estimated, and whether constant alternatives, opt-out or status quo options need to be included. An unlabelled discrete choice experiment was designed by assigning online follow-up visit and offline, in-person follow-up visit as two levels of a generic follow-up mode attribute. A full factorial design would produce a large number of combinations of attribute levels that could not realistically be assessed by a single person. Therefore, a fractional factorial design was chosen to minimise the number of choice sets. In addition, a D-efficiency main effects design was created to maximise relative D-efficiency and improve design efficiency. Attribute interactions are not considered here because it is not clear which attributes may potentially interact, and including interactions would lead to more choice sets. A total of 36 choice sets were ultimately developed, each of which included an extra opt-out option for enhancing the realism of the choice scenarios, in addition to the two follow-up visit alternatives. In addition, to reduce respondent burden, the 36 choice sets were placed into three different versions of the questionnaire, each containing 12 choice sets and one repeat DCE choice set to test the internal consistency of respondents' choices.

An example of a DCE choice set is shown in Figure 2. The choice scenario for respondents is described as follows:

Suppose you recently visited a hospital for a non-urgent mild common or chronic illness (e.g., chronic gastritis, skin disease, etc.) and now you feel that your body is experiencing symptoms similar to those you had before, but they are not serious. At this point, you would like to make an appointment with a doctor for an outpatient follow-up visit. You can access the public Internet hospital through the WeChat application or the hospital application, and make an appointment for an online outpatient follow-up visit through image-text consultation, voice (phone) consultation, and video consultation, or go directly to the hospital for an offline, in-person follow-up visit.

Attribute	Appointment A	Appointment B	None
Cost (CNY)	25	50	Neither A nor B
Mode of follow-up consultation	Offline in-person follow-up visit	Online outpatient follow-up visit	
Choice of follow-up doctor	Non-initial diagnostician at the hospital of initial diagnosis	The patient's own initial diagnostician	
Waiting time for an appointment	0 day/ Today	7 days	
Waiting time on appointment day	30 minutes	60 minutes	
Payment method	Payment without medical insurance	Payment with medical insurance	
Prefer	☐ Appointment A	☐ Appointment B	☐ None

Figure 2. An example of a DCE choice set.

2.4. Survey

The appropriate sample size depends on the form of the question, the complexity of the chosen task, the precision of the expected outcome, the degree of heterogeneity of the target population, the availability of respondents, and the need to conduct subgroup analyses [15,36]. It has been common for researchers to estimate sample sizes based on the number of attribute levels [15]. As in other DCE studies, the minimum sample size in this study is determined using the following equation [37]:

$$N > \frac{500c}{a \times t}$$

When considering main effects, c is equal to the maximum number of levels for any one attribute. N is the number of respondents, t is the number of choice tasks, and a is the number of alternatives for each task (not including the opt-out option). It is calculated that an acceptable sample for this study should include a minimum of 189 respondents, with a minimum of 63 respondents for each version of the questionnaire. Given the percentage of invalid responses and in order to analyse the heterogeneity of preferences, the data collection was carried out with a larger target sample size.

The overall questionnaire consists of three parts. The first part includes four validated scales to capture potential personal characteristics that may influence respondents' preferences: the Risk Attitude Scale (RA) [38], the Online Privacy Concern Scale (OPC) [39], the eHealth Literacy Scale (EHEAL) [40], and the Healthcare Technology Self-Efficacy Scale (HTSE) [41]. The second part presents 13 DCE tasks, consisting of 12 formal DCE choice sets and 1 repeated choice set. The third part collects 13 questions on respondents' personal information such as gender, age, and monthly income.

The formal survey was finally conducted between November 2023 and December 2023 for the general population. The Chinese general population sample was recruited online by a market research company, and the sample participants were relatively representative of the Chinese adult population in terms of age (over 18 years old) and gender. Our research team created an electronic questionnaire with three versions that were identical except for the DCE question. Respondents who clicked on the link to the questionnaire were

randomly assigned to one of the three versions, and each respondent could only complete the questionnaire once. Respondents were first read basic information about the survey and given informed consent. Respondents who did not agree to participate in the survey were instructed to opt out, and those who agreed to participate were formally admitted to the questionnaire. Respondents first answered the four scale questions, then read a brief introduction explaining the DCE attribute levels and tasks, followed by the 13 DCE questions, one of which was an internal validity test question. Finally, respondents answered questions about their socio-demographics and previous experience with telehealth.

2.5. Data Analysis

Mixed logit (MXL) and latent class (LC) models were used to analyse the DCE data. Conditional logit (CL) and multinomial logit (MNL) models are the classic discrete choice models used to model choice. Similar to CL, MNL makes the same statistical assumptions [17,30]: (i) independence of irrelevant alternatives (IIA); (ii) the error terms follow a type-1 extreme value distribution and are independent and identically distributed (IID); and (iii) the homogeneity of respondents' preferences. However, MNL is typically used to describe models that relate choice to individual characteristics of the respondent (explanatory variables may include individual characteristics in addition to the level of attributes of the alternatives), whereas conditional logit typically models choice with the level of attributes of the alternatives (explanatory variables typically include only the level of attributes of the alternatives). These assumptions can be restrictive in describing choice behaviour, so researchers continue to develop more realistic choice models. In recent years, the MXL model has become one of the more flexible discrete choice models and is now widely used [19,21,23]. MXL is a generalization of MNL that relaxes the IIA assumption, accommodates the panel nature of DCE data by allowing for correlation of the subjects who have made repeated choices, and captures the heterogeneity of preferences across individuals by allowing model coefficients to vary across respondents [42].

Although MXL can identify attributes and attribute levels where significant preference differences exist, it does not explain such differences in depth [43]. Therefore, a LC was further modelled to identify groups with similar preferences within the sample and to assess preference heterogeneity across groups. In the LC, respondents are classified into a latent number of classes and preference coefficients are estimated for respondents in each class. The number of latent classes is typically determined using measures of model fit, such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Consistent Akaike Information Criterion (CAIC), as well as the interpretability of the results [17,44,45]. The preferences of respondents belonging to the same class are homogeneous but differ between classes. The data collected are coded using a dummy coding approach [46]. The independent variables in the model are the levels of each attribute in each service alternative. The dependent variable is the choice of each service alternative, which is coded as 1 if the service alternative is chosen and 0 if it is not.

A total of four models were constructed, including three mixed logit models and one latent class model. First, a main effects model was estimated by treating the cost attribute as a continuous variable with fixed effects, and the independent variables included only the attribute levels of the alternative. This was to estimate the main effects of the attribute levels of the alternative on the choice of follow-up service and to calculate the marginal willingness to pay. Second, an interaction model was constructed based on the first main effects model by adding interaction terms between the attribute levels and individual characteristics to test the effects of socio-economic factors and latent variables on respondents' choice decisions. Third, another main effects model was estimated to assess the relative importance of all attributes by treating the cost attribute as a categorical variable with random effects instead of a continuous variable with fixed effects. Finally, still treating the cost attribute as a categorical variable, a latent class model was estimated to identify heterogeneous group preferences.

Significant coefficients estimated from the models indicate that a particular attribute level has an impact on respondents' choices. Attribute level coefficients can be interpreted as the relative strength or preference weight of each attribute level. Positive and negative coefficients reflect the direction of influence of a particular attribute level on the choice decision, with positive coefficients indicating a positive influence and negative coefficients indicating a negative preference. The value of the coefficients reflects the extent to which a particular attribute level influences the choice decision; the larger the coefficient is, the higher the utility and the greater the preference weight.

3. Results

3.1. Sample Characteristics

After excluding respondents who failed the internal validity test, we received questionnaires from a total of 311 respondents. Among these online recruited respondents, the number of men was slightly lower than the number of women (men: 46.0%, women: 54.0%), and the majority of them were between 30 and 49 years old (71.0%). A total of 94.2% of the respondents lived in cities, the majority of them had a full-time job (86.8%), and more than half of them (59.8%) had a bachelor's degree or higher education level. Almost all respondents (98.7%) had medical insurance, and about half (55.9%) had experience of using the Internet to seek medical care. In addition, almost a third of respondents (35.4%) had chronic diseases. Almost half of respondents (49.8%) stated a high level of knowledge about public Internet hospitals, and about three quarters (74.6%) reported a high level of trust in public Internet hospitals. Specific respondent-related information is shown in Table 2. Detailed information and statistical results for the Risk Attitude Scale (RA), the Healthcare Technology Self-Efficacy Scale (HTSE), the eHealth Literacy Scale (EHEAL), and the Online Privacy Concern Scale (OPC) are shown in Tables A1–A4 in Appendix A.

Table 2. Demographic characteristics (N = 311).

Characteristic	Frequency (Percentage)
Gender	
Male	143 (46.0%)
Female	168 (54.0%)
Age	
18–29	49 (15.8%)
30–39	113 (36.3%)
40–49	108 (34.7%)
50–59	18 (5.8%)
>60	23 (7.4%)
Residence	
Town/city	293 (94.2%)
Rural areas	18 (5.8%)
Education	
Junior high school and below	12 (3.9%)
High school	39 (12.5%)
University colleges (including those studying)	74 (23.8%)
Bachelor's degree (including those studying)	168 (54.0%)
Master's degree (including those studying)	15 (4.8%)
PhD (including those studying)	3 (1.0%)
Occupation	
Self-employed	15 (4.8%)
Full-time employment	270 (86.8%)
Part-time employment	4 (1.3%)
Retirement	20 (6.4%)
Other	2 (0.6%)

Table 2. Cont.

Characteristic	Frequency (Percentage)
Monthly income (CNY)	
≤3000	10 (3.2%)
3001–6000	78 (25.1%)
6001–9000	102 (32.8%)
9001–12,000	73 (23.5%)
12,001–15,000	34 (10.9%)
>15,000	14 (4.5%)
Medical insurance	
Yes	307 (98.7%)
No	4 (1.3%)
Knowledge of public Internet hospitals	
Very little	10 (3.2%)
Less	31 (10.0%)
General	115 (37.0%)
More	140 (45.0%)
A lot	15 (4.8%)
Trust in public Internet hospitals	
Very little	1 (0.3%)
Less	7 (2.3%)
General	71 (22.8%)
More	193 (62.1%)
A lot	39 (12.5%)
Internet healthcare experience	
Yes	174 (55.9%)
No	137 (44.1%)
Perceived health status	
Very good	19 (6.1%)
Good	167 (53.7%)
General	109 (35.0%)
Poor	15 (4.8%)
Very poor	1 (0.3%)
Number of hospital visits in the past year	
≤3	190 (61.1%)
4–6	101 (32.5%)
7–9	15 (4.8%)
≥10	5 (1.6%)
Chronic diseases	
Yes	110 (35.4%)
No	201 (64.6%)

3.2. Results of Mixed Logit Model

3.2.1. Analysis of Respondents' Preferences

The results of the MXLs for main effects and interaction effects estimated with cost attributes as continuous variables are shown in Table 3 (where only significant interaction terms were retained in the interaction effects model). All random parameters were assumed to be normally distributed and 500 Halton draws were used for all MXLs. In the main effects model, the mean coefficients are significant for all attribute levels. The *p*-values for the attribute levels were typically as low as <0.001, except for the online follow-up mode. In addition, the standard deviation (SD) estimates that were statistically significant in the main effects models indicated significant preference heterogeneity for attribute levels among respondents in the sample. A positive coefficient for an attribute level indicates that the respondent has a positive preference for that attribute level relative to the reference attribute level. Conversely, a negative coefficient for an attribute level reflects a negative preference for that attribute level relative to the reference attribute level.

Table 3. Results of mixed logit model for main effects and interaction effects (cost as continuous variable).

Variables	Main Effects Model		Interaction Effects Model	
	Coefficient	<i>p</i> -Value	Coefficient	<i>p</i> -Value
Mean				
Cost	−0.051	<0.001	−0.052	<0.001
Mode Online	−0.264	0.001	−1.218	0.156
NIDocIHos	0.273	<0.001	0.276	<0.001
Initial Doc	1.220	<0.001	1.236	<0.001
3 Days	0.894	<0.001	0.906	<0.001
0 Day	1.987	<0.001	2.018	<0.001
30 Min	0.470	<0.001	0.480	<0.001
10 Min	0.874	<0.001	0.891	<0.001
With MI	0.926	<0.001	0.945	<0.001
Opt-out	−2.313	<0.001	−2.311	<0.001
Mode Online*Age 30–39			−0.474	0.092
Mode Online*Age ≥ 50			−0.924	0.016
Mode Online*Noexperience			−0.349	0.086
Mode Online*HTSE			0.223	0.057
SD				
Mode Online	0.908	<0.001	0.887	<0.001
Initial Doc	1.627	<0.001	1.651	<0.001
0 Day	1.435	<0.001	1.465	<0.001
10 Min	0.566	<0.001	0.585	<0.001
With MI	1.098	<0.001	1.122	<0.001
Opt-out	3.434	<0.001	3.382	<0.001

According to Table 3, the results of the main effects model show that Chinese respondents generally preferred a traditional, offline, in-person follow-up visit at the hospital to an online outpatient follow-up visit provided by a public Internet hospital (coefficient = −0.264, $p < 0.001$). Respondents had a higher preference for the low cost of the service, availability of an immediate appointment, shorter waiting time for consultation on the day of the appointment, use of medical insurance to pay for the service, and outpatient follow-up visits provided by their own initial diagnostician.

The results of the interaction effects model in Table 3 show that the group aged 30–39 years (coefficient = −0.474, $p = 0.092$) and respondents aged 50 years and over (coefficient = −0.924, $p = 0.016$) were relatively less likely to choose the option of using Internet hospitals for online outpatient follow-up visits. People with no experience of using Internet healthcare also had a relatively low preference for online outpatient follow-up visits (coefficient = −0.349, $p = 0.086$). However, respondents with higher healthcare technology self-efficacy were relatively more receptive to online outpatient follow-up visits (coefficient = 0.223, $p = 0.057$).

3.2.2. Analysis of Respondents' Willingness to Pay

Based on the results of the main effects mixed logit model in Table 3, respondents' willingness to pay for a change from the reference level of an attribute to other levels of the same attribute was measured by the coefficient of other non-cost attribute levels divided by the coefficient of the cost attribute. Respondents' average willingness to pay and 95% confidence interval (CI) estimates are shown in Table 4. The negative WTP for changing from an offline, in-person follow-up visit to an online remote outpatient follow-up visit indicated that these Chinese respondents generally preferred traditional, in-person follow-up visits to online outpatient follow-up visits, and that they were willing to pay CNY 5.150 to avoid the change from an offline, in-person follow-up visit to an online outpatient follow-up visit. A positive WTP indicates that respondents would be willing to pay a certain amount to achieve a change from the reference level to the current level of the attribute. They were willing to pay CNY 5.337 for follow-up consultations provided

by non-initial diagnostician at the hospital where they were initially diagnosed, and CNY 23.840 for follow-up consultations provided by their own initial diagnostician. Meanwhile, Chinese respondents were willing to pay CNY 17.457 to reduce the waiting time for an appointment from 7 days to 3 days and CNY 38.815 to reduce the waiting time for an appointment from 7 days to 0 days. Similarly, they were willing to pay CNY 9.174 if the waiting time on the day of the appointment was reduced from 60 min to 30 min, and CNY 17.072 if the waiting time on the day of the appointment was reduced from 60 min to 10 min. Finally, they were also willing to pay CNY 18.091 to change the payment method from payment without medical insurance to payment with medical insurance.

Table 4. WTP for the full sample.

Attribute and Level	WTP (China CNY)		[95% CI]
Mode of follow-up consultation			
Mode Offline–Mode Online	−5.150	−8.225	−2.075
Choice of follow-up doctor			
NIDocNIHos–NIDocIHos	5.337	2.459	8.215
NIDocNIHos–Initial Doc	23.840	18.943	28.736
Waiting time for an appointment			
7 Days–3 Days	17.457	14.435	20.480
7 Days–0 Day	38.815	33.855	43.774
Waiting time on appointment day			
60 Min–30 Min	9.174	5.943	12.405
60 Min–10 Min	17.072	13.574	20.570
Payment method			
Without MI–With MI	18.091	14.630	21.552

3.2.3. Analysis of the Relative Importance of Attributes

Table 5 and Figure 3 show the results of the main effects MXL estimated with the cost attribute as categorical variable. The relative importance of an attribute is calculated as the difference between the maximum level utility and the minimum level utility of that attribute divided by the sum of the difference between the maximum level utility and the minimum level utility of all attributes. Based on the attribute level coefficients in Table 5, the relative importance of each attribute in the respondents' decision to choose an outpatient follow-up appointment was calculated and the results are shown in Figure 4. Figures 3 and 4 show that lower cost of services had the greatest influence on respondents' choice of follow-up appointments, followed by shorter waiting time for appointments and the provision of continuous follow-up services by the same doctor who initially diagnosed the patient. The relative importance of payment with medical insurance was slightly higher than waiting 10 min on the day of the appointment. Respondents seemed to consider the mode of follow-up consultation (offline, in-person follow-up visit or online outpatient follow-up visit) as the relatively least important attribute. This may be a preliminary indication that Chinese respondents are willing to exchange an offline, in-person follow-up visit and an online outpatient follow-up visit if their preferences for other attribute levels are satisfied, particularly lower cost, shorter waiting time for available appointments, and continuity of follow-up doctor.

Table 5. Results of mixed logit model for main effects (cost as categorical variable).

Variable	Coefficient	p-Value	[95% conf. interval][95% CI]	
Mean				
Cost 25	−0.860	<0.001	−1.038	−0.681
Cost 50	−2.462	<0.001	−2.796	−2.129
Mode Online	−0.303	0.001	−0.484	−0.121
NIDocIHos	0.326	<0.001	0.151	0.501
Initial Doc	1.424	<0.001	1.124	1.725

Table 5. Cont.

Variable	Coefficient	p-Value	[95%conf.interval]	[95% CI]
3 Days	1.069	<0.001	0.868	1.270
0 Day	2.366	<0.001	2.059	2.673
30 Min	0.458	<0.001	0.273	0.642
10 Min	0.939	<0.001	0.737	1.140
With MI	1.146	<0.001	0.942	1.351
Opt-out	−1.595	<0.001	−2.303	−0.888
SD				
Cost 50	1.705	<0.001	1.393	2.018
Mode Online	1.010	<0.001	0.779	1.242
NIDocIHos	0.382	0.019	0.063	0.700
Initial Doc	1.885	<0.001	1.567	2.203
3 Days	0.497	0.006	0.141	0.853
0 Day	1.486	<0.001	1.199	1.773
10 Min	−0.720	<0.001	−1.067	−0.374
With MI	1.217	<0.001	0.996	1.438
Opt-out	3.201	<0.001	2.587	3.815

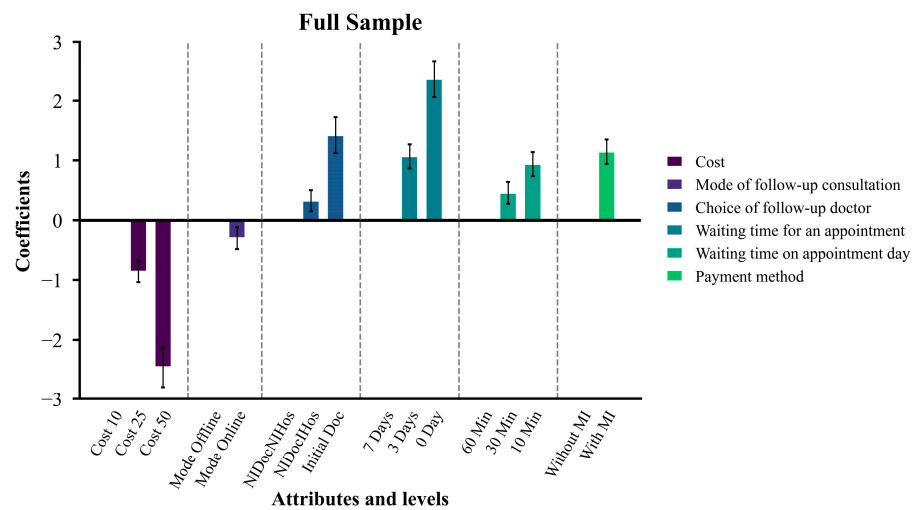


Figure 3. Attribute level preference weights for the full sample.

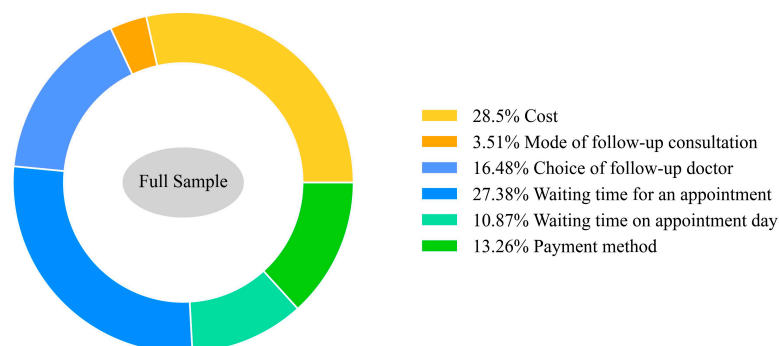


Figure 4. The relative importance of attributes for the full sample.

3.3. Results of Latent Class Model

In addition to the attribute levels, 6 categorical and 4 continuous variables, for a total of 10 respondent-related characteristics, were included in the latent class model to determine the optimal number of categories. The six binary variables were coded using dummy codes, and the reference groups were as follows: male, aged 18–29, less than a bachelor's degree, income of CNY 9000 and less, experience with Internet health, and no chronic diseases. Among them, “Female” indicates female, “Age 30–39” indicates

30–39 years old, “Age 40–49” indicates 40–49 years old, “Age $\geq$ 50” indicates 50 years old and above, “Edu $\geq$ Bachelor” indicates bachelor degree and above, “Income > 9000” indicates income over 9000 CNY, “Noexperience” indicates no experience with Internet health, and “Yeschronic” indicates having chronic diseases. “RA”, “HTSE”, “EHEAL” and “OPC” are four continuous variables indicating risk attitude score, healthcare technology self-efficacy score, eHealth literacy score and online privacy concern score, respectively.

As shown in Table 6, after a comprehensive comparison of AIC, BIC, CAIC, and interpretability of the results, a total of three main classes were identified by the LC model. Respondents’ preference weights for different attribute levels in each of the three classes are plotted separately, see Figure 5a–c. And the relative importance of different attributes in the three classes is shown in Figure 6a–c. The sample in the first class accounted for the largest proportion of the total sample at 59.5%, and respondents in this class showed a preference for traditional, in-person follow-up visits, with low cost being the most important to them, followed by short waiting time for appointments, continuity of the follow-up practitioner, payment with medical insurance, short waiting time on appointment day, and mode of traditional, in-person follow-up visits.

Table 6. The results of latent class model.

Variable	Class 1		Class 2		Class 3	
	Coefficient	<i>p</i> -Value	Coefficient	<i>p</i> -Value	Coefficient	<i>p</i> -Value
Mean						
Cost 25	−0.462	<0.001	−0.726	0.004	−0.752	<0.001
Cost 50	−1.340	<0.001	−0.887	<0.001	−1.820	<0.001
Mode Online	−0.254	<0.001	−0.278	0.109	0.197	0.093
NIDocIHos	0.078	0.280	0.726	0.001	0.265	0.085
Initial Doc	0.364	<0.001	3.539	<0.001	0.466	0.008
3 Days	0.686	<0.001	−0.071	0.762	0.807	<0.001
0 Day	1.268	<0.001	0.133	0.639	2.385	<0.001
30 Min	0.287	<0.001	0.311	0.170	0.474	0.002
10 Min	0.542	<0.001	0.586	0.007	0.698	<0.001
With MI	0.557	<0.001	1.489	<0.001	0.937	<0.001
Opt-out	−5.354	<0.001	1.174	0.003	1.469	<0.001
Female	−0.286	0.383	0.158	0.735	—	—
Age 30–39	0.097	0.861	−0.200	0.798	—	—
Age 40–49	−0.331	0.523	−0.597	0.409	—	—
Age $\geq$ 50	0.534	0.495	0.007	0.994	—	—
Edu $\geq$ Bachelor	0.583	0.107	−0.307	0.536	—	—
Income > 9000	−0.078	0.818	0.026	0.957	—	—
Noexperience	0.291	0.465	−0.169	0.757	—	—
Yeschronic	0.246	0.473	0.419	0.358	—	—
RA	0.381	0.034	0.106	0.666	—	—
HTSE	0.209	0.383	0.366	0.260	—	—
EHEAL	−0.005	0.990	−0.985	0.069	—	—
OPC	0.219	0.107	0.128	0.512	—	—
Constant	−2.316	0.220	1.054	0.686	—	—

The second class of the sample was the smallest, at 17.1%, and respondents in this class did not show a significant preference for either the traditional in-person follow-up visit or the online outpatient follow-up visit; however, they did place a high value on the continuity of the follow-up visit. The second most important attribute was the payment with medical insurance, followed by the low cost, short waiting time on appointment day, mode of follow-up consultation, and short waiting time for appointments. This may indicate that these respondents did not explicitly state a single preference for a particular mode of follow-up consultation and that continuity of follow-up visits had a strong influence on their choice, followed by payment with medical insurance. These respondents are more likely to choose a follow-up option that offers access to their initial diagnostician

or payment with medical insurance to cover the cost of care, regardless of whether the follow-up mode is an offline in-person visit to a physical hospital or an online outpatient follow-up visit provided by a public Internet hospital. The p-value for waiting time for an appointment was not significant and was the least important in relative importance, which may indicate that the second group of respondents were willing to sacrifice speed of access to care for attributes such as continuity of care and payment with medical insurance, which respondents considered more important than waiting time for an appointment.

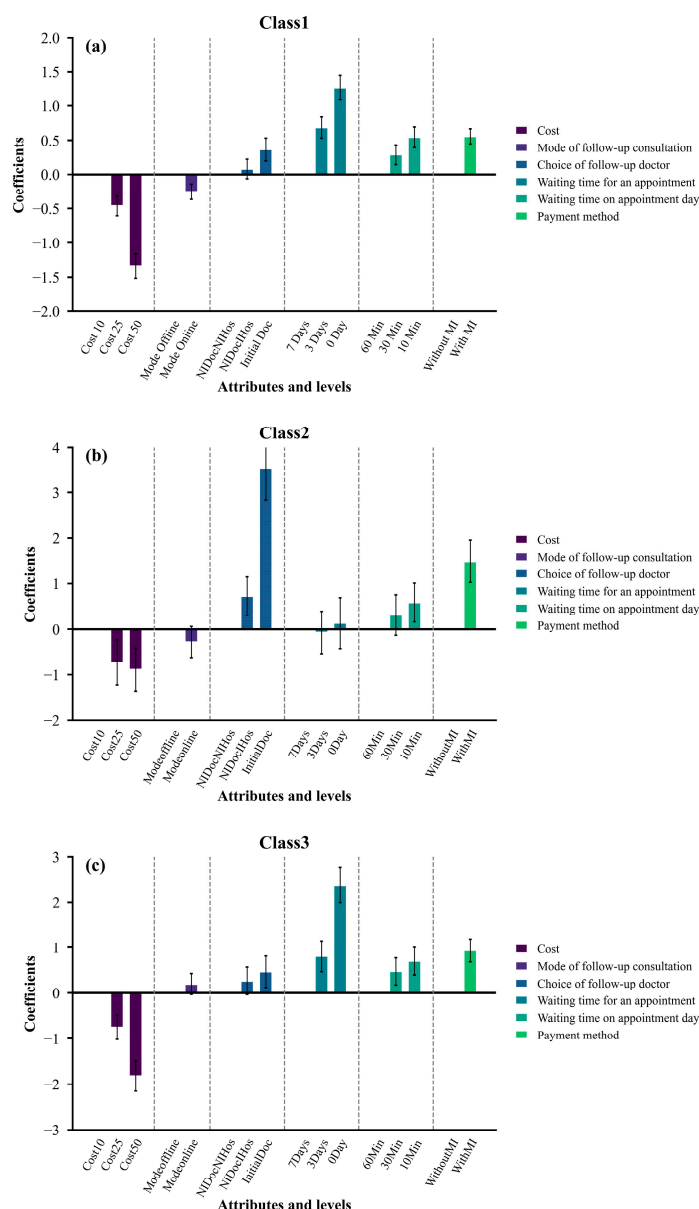


Figure 5. Attribute level preference weights for the three classes. (a) Preference weights for respondents in class 1; (b) Preference weights for respondents in class 2; and (c) Preference weights for respondents in class 3.

The third class of respondents comprised 23.3% of all respondents, and this group showed a significant preference for online outpatient follow-up visits, while they mostly preferred short waiting time for appointments, followed by lower cost, payment with medical insurance, short waiting time on appointment day, continuity of the follow-up practitioner, and mode of traditional, in-person follow-up visits. This suggests that online outpatient follow-up visits may be an attractive alternative to in-person follow-up visits

if public Internet hospitals can offer quick appointments to see a doctor, relatively low appointment cost, and support online payment with medical insurance.

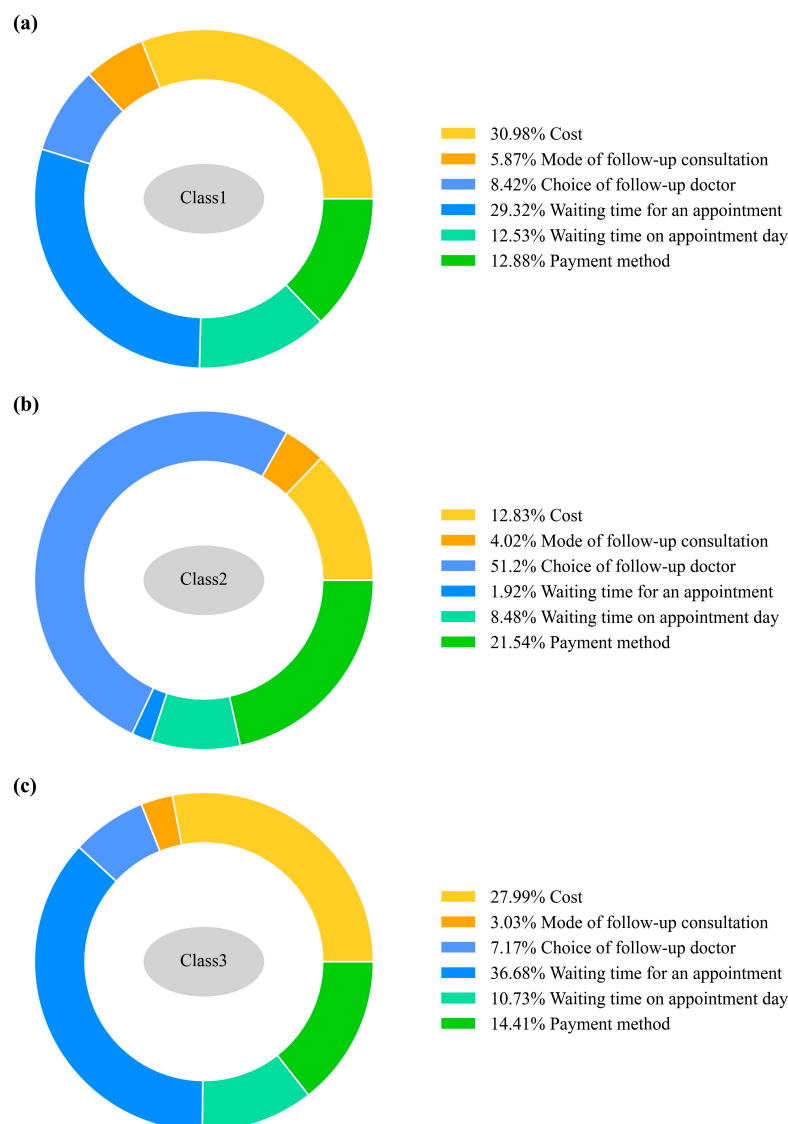


Figure 6. The relative importance of attributes for the three classes. (a) The relative importance of attributes for respondents in class 1; (b) The relative importance of attributes for respondents in class 2; and (c) The relative importance of attributes for respondents in class 3.

In terms of the relative importance of attributes, the three classes of respondents valued cost, continuity of doctor, and waiting time for an appointment most highly. Thus, the three classes of patients can be characterised as: “price-dominant”, “doctor-continuity-dominant” and “time-dominant”. This corresponds to the results of the full sample main effects mixed logit model, which were on average the three most important key attributes for all respondents. In addition, from the perspective of preference for telehealth, the three classes of respondents can be described as: “preference for traditional mode”, “mixed preference”, and “preference for telehealth”.

The demographic test showed that respondents with higher risk attitude scores (the more able to take risks) were more likely to be in the first class compared to respondents in the third class (coefficient = 0.381, $p = 0.034$). Respondents in class 1 were very cost sensitive and were willing to sacrifice improvements in the level of other attributes in exchange for lower cost of healthcare services. In contrast, respondents in class 3 were very sensitive to waiting time for an appointment and were more willing to access care more quickly. From

this point of view, respondents in the first class were more adventurous (more risk taking) than respondents in the third class. Compared to class 3, respondents with higher eHealth literacy were less likely to be in class 2 (coefficient = -0.985 , $p = 0.069$). Respondents in the third class preferred online outpatient follow-up visits, while respondents in the second class did not show a significant preference for offline, in-person follow-up visits or online outpatient follow-up visits.

4. Discussion

4.1. Principal Results

Our study found that, overall, Chinese respondents preferred traditional, in-person follow-up visits to online outpatient follow-up visits through Internet hospitals when choosing the mode of follow-up consultation after the COVID-19 pandemic. Respondents had significant preferences for low cost, seeing their own initial diagnostician, short waiting time for appointments and waiting time on the day of the visit, and payment method with medical insurance. We also found that age, previous telehealth experience, and healthcare technology self-efficacy had an impact on choice preference between offline, in-person follow-up visits and online outpatient follow-up visits. Older people (≥ 50) and those with no telehealth experience were relatively less likely to prefer online outpatient follow-up visits offered by public Internet hospitals, whereas respondents with higher healthcare technology self-efficacy were relatively more likely to accept online outpatient follow-up visits.

Notably, the latent class model identified that a proportion of the population preferred online outpatient follow-up visits, and this preference was statistically significant ($p = 0.093 < 0.1$). The group who stated a preference for online outpatient follow-up visits also valued very short waiting time for appointments and lower cost of services, even over continuity of follow-up visits. This may suggest that there is a proportion of the population who are willing to use telehealth to access healthcare more quickly and pay less for it. There is another group that did not clearly express a significant preference for either mode of follow-up (offline, in-person follow-up visit and online outpatient follow-up visit), but they highly value continuity of follow-up and, subsequently, payment method with medical insurance. This may indicate that if telehealth can meet this group's strong preference for continuity of follow-up and payment method with medical insurance, then they would consider using telehealth.

4.2. Comparison with Prior Work

The study of patient preferences to inform health policy and health system reform is attracting increasing research interest from academics. In particular, as an innovative application of information technology in the medical field, telehealth has not been used adequately and effectively, and it is therefore valuable to investigate the issue of patient preferences for telehealth in order to provide appropriate services in response to patient preferences. As discrete choice experiments have a well-established theoretical basis and are widely used [18–23], it is feasible to use this approach in this study. Lancaster's new approach to consumer theory [47] proposes that the utility of a good is derived from the characteristic attributes of the good, rather than from the good itself. Random utility theory further assumes that the utility function is described by a combination of observable and unobservable attributes and an error term. The principle of utility maximisation assumes that people will choose the good or service that provides the greatest individually perceived utility. In healthcare, patients are consumers and decision-makers who choose the healthcare service option with the greatest utility based on the principle of utility maximisation, and the outcomes of these choices reflect patient preferences. This study followed the methodological specifications of the DCE, and the results complement to some extent the relevant results of previous studies.

Studies on patient preferences for choosing between telehealth and traditional healthcare services have mostly reported cautious attitudes towards telehealth among respondents, who typically show a preference for traditional healthcare service delivery meth-

ods [13,18–23]. This is consistent with our empirical findings. Not surprisingly, the extent to which the same attributes were preferred differed between the research contexts. Our study showed that, on average across all respondents, the top three aspects they valued most were, cost, waiting time for an appointment, and continuity of follow-up appointments. While in the area of primary care consultations, the study by von Weinrich et al. [21] showed that German patients regarded continuity of care as the most important influencing factor, followed by waiting time until the next available appointment. In another study which investigated preferences for initial COVID-19 diagnosis attributes, Chinese respondents valued types of clinics the most, to be followed by reimbursement ratio [23]. In addition, our results also showed that Chinese respondents had the relatively lowest preference weight for the attribute of mode of follow-up consultation, while the results of von Weinrich et al. [21] showed that the relative importance of consultation mode ranked third among the five attributes.

The results of our latent class model, which found that those who preferred online outpatient follow-up visits showed a strong preference for shorter waiting time for an appointment and lower service cost, supports a study by Qureshi et al. [24], who also found that dermatology patients preferred telemedicine if it meant a faster visit to a doctor. Previous studies have confirmed that telehealth has significant benefits in terms of reducing waiting time and cost of care, and our empirical analysis supports these points. The results of our main effects model show that Chinese respondents preferred low service cost the most. A study by Savira et al. [48] also reported that Australian respondents were very price sensitive. In addition, the study by Savira et al. [48] found that face-to-face contact was preferred to telephone or video services, but telemedicine may be attractive to patients if it avoids significant travel and is provided by a doctor known to the patient. These results are similar to those of our study.

Patient attitudes towards the use of telehealth as a complement to traditional healthcare have also been explored in several studies. The survey by Ebbert et al. [49] showed that more than half of patients would be “very likely” to use telehealth services to supplement their medication and almost three quarters would be “somewhat” or “very likely” to use telehealth to manage a long-term health problem. A cross-sectional survey by Rasmussen et al. [50] showed that the majority of patients agreed that telehealth is an acceptable way to receive health services and improve access to care. The findings of Toll et al. [51] suggest that consumers do not want to see telehealth as a complete replacement for face-to-face care, but value its availability, the choice, and the flexibility to use telehealth when it suits them. Our results also show that while Chinese respondents are generally cautious about telehealth, the benefits of telehealth in terms of shorter waiting times for appointments and reduced healthcare cost are also preferred by some patients.

Patients with a strong preference for short waiting time for appointments and low cost prefer online outpatient follow-up visits, which may indicate that telehealth is a viable alternative to traditional in-person visits for receiving healthcare services, as long as telehealth meets patients’ needs and preferences for faster and cheaper access to care. Technological challenges and lack of physical examination are the main limitations of telehealth [52]. Several studies have compared the diagnostic accuracy of telehealth and traditional healthcare. Watson et al. [53] found that clinical outcomes for acne patients followed up via an asynchronous remote e-visit platform were comparable to traditional outpatient visits. Hertzog et al. [54] found that diagnostic accuracy was comparable between telemedicine and face-to-face visits for less severe conditions. According to a review [55], telemedicine appeared to be equivalent to face-to-face care in most cases. These studies show that the diagnostic accuracy between face-to-face visits and telehealth is almost equivalent in non-emergency medical situations, which means that telehealth can be used as an alternative to traditional healthcare service solutions in certain medical scenarios to meet people’s healthcare needs.

Additionally, the results of the interaction model reflect the effect of demographic characteristics on patient preferences. The effect of individual related variables on preferences

has also been verified in other literature. The study by Chudner et al. [20] showed that younger patients and those with experience of video calling preferred video consultations to in-clinic consultations. The study by von et al. [21] showed that participants with fewer privacy concerns and greater technological proficiency preferred video consultations to in-clinic consultations. Chen et al. [11] and Ebbert et al. [49] have observed gender differences in preferences for telehealth. Specifically, Chinese male elderly respondents were strongly inclined to use telehealth solutions, while female elderly respondents preferred traditional medical solutions [11]. Men were less likely to prefer telehealth services for reviewing test results or mental health issues [49].

4.3. Policy Implications

These findings are particularly significant because they may suggest several aspects that Chinese Internet hospitals need to focus on in the future as they strive to improve the quality and satisfaction of online outpatient follow-up services, among other things. First, patients who prefer remote follow-up consultation are willing to sacrifice continuity of follow-up in exchange for faster follow-up appointments and lower service cost, so healthcare providers need to manage the scheduling and cost of telehealth services as reasonably as possible. Second, if the online outpatient follow-up visit is provided by the patient's initial diagnostician, it may also attract some patients who are willing to choose an online follow-up visit. This suggests the importance of establishing a good doctor–patient relationship, especially in the context of telehealth service delivery. Furthermore, enabling online payment with medical insurance and developing reimbursement policies specific to telehealth are also worthy priorities to be explored.

4.4. Limitations

Methodologically, DCE is limited by the number of attributes and levels of attributes; too many attributes and levels of attributes would create a more complex choice experiment design, making it difficult for subjects to make trade-offs. Therefore, this study currently only explores the effects of six key attributes on respondents' choices, and there may be other influencing factors that we have not considered. In terms of data collection, this DCE recruited a group of online subjects through an online survey implemented by posting the created electronic questionnaire on a web-based platform. These respondents have some internet skills, few live in rural areas, and on average have a high level of education and therefore may not be broadly representative of the general population in China. In addition, the relatively small number of respondents aged 50 and over in our sample may limit the generalisability of the interpretation of the results regarding the effect of age on patient preferences. Future work should consider increasing the sample size and conducting subgroup analyses to better understand and compare the preferences of different groups for telehealth. There is also a need to segment the study population to explore the preferences and attitudes of the elderly or rural residents towards telehealth as an innovative mode of healthcare delivery, as they may also be most in need of easily accessible services.

5. Conclusions

To the best of our knowledge, this is the first discrete choice experiment conducted in China after the COVID-19 pandemic to investigate Chinese patients' preferences for online outpatient follow-up visits provided by public Internet hospitals versus offline, in-person follow-up visits. The results of this study suggest that cost, mode of follow-up consultation, choice of follow-up doctor, waiting time for an appointment, waiting time on appointment day, and payment method are all important factors in the choice of follow-up consultation. Chinese patients were very concerned about the cost of follow-up services, waiting time for an appointment, and continuity of follow-up visits. On average, respondents showed a relatively stronger preference for traditional, offline, and in-person follow-up visits than for remote, online outpatient follow-up visits offered by public Internet hospitals. However, there is a segment of the population that shows a preference for online outpatient

follow-up visits, and this group strongly avoids long waiting time for an appointment and high cost. This is a preliminary indication that Chinese people are generally more cautious about telehealth, but it may be an attractive option for patients who need relatively inexpensive care in a short time. In addition, patients who highly value continuity of care may also be motivated to use online follow-up service if it is provided by a provider with whom the patient is familiar or has an established relationship. This suggests that Chinese Internet hospitals need to consider patients' priorities for continuity of care when providing telehealth services. In summary, telehealth service delivery plans need to be optimised in conjunction with information on the preferences and priorities of the target population to meet their needs and preferences. Combining telehealth services with traditional healthcare to provide integrated online and offline healthcare services to patients is promising and deserves further exploration.

Our findings have important practical implications. First, our findings can provide information for telehealth policy making. This study found that three important factors influencing patients' choice of healthcare services are cost, time, and continuity of care. And the advantages of telehealth lie in reducing cost and improving access to healthcare. This suggests that the development of telehealth is promising. For policymakers and providers of health services, there is a need to regulate and control the price of services and extend the coverage of medical insurance. For healthcare practices, it is necessary to further expand the content of services suitable for online operation and optimise the process of medical treatment. Second, our findings can inform healthcare practices to design patient-centred, integrated traditional and telehealth services based on patients' preferences and priorities. Healthcare providers need to measure patient preferences for telehealth attributes in order to design successful telehealth services. Healthcare practices can improve patient satisfaction with telehealth services by addressing patient needs and preferences for cost of care, waiting time and quality of care. Internet hospitals can reasonably schedule the appointment time for online doctors, as well as adjust the opening time and number of online appointments to maximise the role of telehealth in improving patient accessibility and increasing the convenience of medical treatment. Patients with mixed service mode preferences (no significant preference for traditional visits or telehealth visits) place a high value on continuity of care, suggesting that patient preferences for continuity need to be considered in the design and delivery of combined online and offline services.

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Appendix A

The results of the Risk Attitude Scale (RA), the Healthcare Technology Self-Efficacy Scale (HTSE), the eHealth Literacy Scale (EHEAL), and the Online Privacy Concern Scale (OPC) are shown in Tables A1–A4, respectively.

Table A1. The results of the Risk Attitude Scale (N = 311).

Item	Frequency (Percentage)
Q1: Drinking heavily at a social function.	
Extremely Unlikely	138 (44.4%)
Moderately Unlikely	70 (22.5%)
Somewhat Unlikely	44 (14.1%)
Not Sure	11 (3.5%)
Extremely Likely	34 (10.9%)
Moderately Likely	9 (2.9%)
Somewhat Likely	5 (1.6%)
Q2: Engaging in unprotected sex.	
Extremely Unlikely	109 (35.0%)
Moderately Unlikely	84 (27.0%)
Somewhat Unlikely	36 (11.6%)
Not Sure	29 (9.3%)
Extremely Likely	28 (9.0%)
Moderately Likely	20 (6.4%)
Somewhat Likely	5 (1.6%)
Q3: Driving a car without wearing a seat belt.	
Extremely Unlikely	200 (64.3%)
Moderately Unlikely	60 (19.3%)
Somewhat Unlikely	24 (7.7%)
Not Sure	7 (2.3%)
Extremely Likely	14 (4.5%)
Moderately Likely	4 (1.3%)
Somewhat Likely	2 (0.6%)
Q4: Riding a motorcycle without a helmet.	
Extremely Unlikely	129 (41.5%)
Moderately Unlikely	78 (25.1%)
Somewhat Unlikely	48 (15.4%)
Not Sure	15 (4.8%)
Extremely Likely	23 (7.4%)
Moderately Likely	14 (4.5%)
Somewhat Likely	4 (1.3%)
Q5: Sunbathing without sunscreen.	
Extremely Unlikely	44 (14.1%)
Moderately Unlikely	60 (19.3%)
Somewhat Unlikely	42 (13.5%)
Not Sure	42 (13.5%)
Extremely Likely	72 (23.2%)
Moderately Likely	36 (11.6%)
Somewhat Likely	15 (4.8%)
Q6: Walking home alone at night in an unsafe area of town.	
Extremely Unlikely	51 (16.4%)
Moderately Unlikely	88 (28.3%)
Somewhat Unlikely	57 (18.3%)
Not Sure	37 (11.9%)
Extremely Likely	55 (17.7%)
Moderately Likely	16 (5.1%)
Somewhat Likely	7 (2.3%)

Table A2. The results of the Healthcare Technology Self-Efficacy Scale (N = 311).

Item	Frequency (Percentage)
Q1: It is easy for me to use internet health services.	
Strongly Disagree	1 (0.3%)
Very Disagree	1 (0.3%)
Somewhat Disagree	10 (3.2%)
General	32 (10.3%)
Somewhat Agree	116 (37.3%)
Very Agree	109 (35.0%)
Strongly Agree	42 (13.5%)
Q2: I feel uncomfortable to use internet health services.	
Strongly Disagree	45 (14.5%)
Very Disagree	88 (28.3%)
Somewhat Disagree	109 (35.0%)
General	48 (15.4%)
Somewhat Agree	12 (3.9%)
Very Agree	7 (2.3%)
Strongly Agree	2 (0.6%)
Q3: I am very confident in my abilities to use internet health services.	
Strongly Disagree	2 (0.6%)
Very Disagree	3 (1.0%)
Somewhat Disagree	9 (2.9%)
General	38 (12.2%)
Somewhat Agree	91 (29.3%)
Very Agree	109 (35.0%)
Strongly Agree	59 (19.0%)
Q4: I would be able to use internet health services without much effort.	
Strongly Disagree	2 (0.6%)
Very Disagree	4 (1.3%)
Somewhat Disagree	11 (3.5%)
General	46 (14.8%)
Somewhat Agree	105 (33.8%)
Very Agree	101 (32.5%)
Strongly Agree	42 (13.5%)

Table A3. The results of the eHealth Literacy Scale (N = 311).

Item	Frequency (Percentage)
Q1: I know how to find helpful health resources on the Internet	
Strongly Disagree	0 (0%)
Disagree	11 (3.5%)
Undecided	63 (19.9%)
agree	189 (60.8%)
Strongly agree	49 (15.8%)
Q2: I know how to use the Internet to answer my health questions	
Strongly Disagree	2 (0.6%)
Disagree	12 (3.9%)
Undecided	46 (14.8%)
agree	140 (45.0%)
Strongly agree	111 (35.7%)
Q3: I know what health resources are available on the Internet	
Strongly Disagree	2 (0.6%)
Disagree	11 (3.5%)
Undecided	49 (15.8%)
agree	160 (51.4%)
Strongly agree	89 (28.6%)

Table A3. *Cont.*

Item	Frequency (Percentage)
Q4: I know where to find helpful health resources on the Internet	
Strongly Disagree	0 (0%)
Disagree	18 (5.8%)
Undecided	45 (14.5%)
agree	172 (55.3%)
Strongly agree	76 (24.4%)
Q5: I know how to use the health information I find on the Internet to help me	
Strongly Disagree	0 (0%)
Disagree	7 (2.3%)
Undecided	44 (14.1%)
agree	166 (53.4%)
Strongly agree	94 (30.2%)
Q6: I have the skills I need to evaluate the health resources I find on the Internet	
Strongly Disagree	6 (1.9%)
Disagree	28 (9.0%)
Undecided	76 (24.4%)
agree	129 (41.5%)
Strongly agree	72 (23.2%)
Q7: I can tell high quality from low quality health resources on the Internet	
Strongly Disagree	5 (1.6%)
Disagree	35 (11.3%)
Undecided	104 (33.4%)
agree	128 (41.2%)
Strongly agree	39 (12.5%)
Q8: I feel confident in using information from the Internet to make health decisions	
Strongly Disagree	3 (1.0%)
Disagree	27 (8.7%)
Undecided	78 (25.1%)
agree	123 (39.5%)
Strongly agree	80 (25.7%)

Table A4. The results of the Online Privacy Concern Scale (N = 311).

Item	Frequency (Percentage)
Q1: Are you concerned that you are asked for too much personal information when you register or make online purchases?	
Fully concerned	8 (2.6%)
Rather concerned	44 (14.1%)
Neither concerned nor not concerned	56 (18.0%)
Rather not concerned	141 (45.3%)
Not at all concerned	62 (19.9%)
Q2: Are you concerned that an email you send may be read by someone else besides the person you sent it to?	
Fully concerned	26 (8.4%)
Rather concerned	41 (13.2%)
Neither concerned nor not concerned	64 (20.6%)
Rather not concerned	118 (37.9%)
Not at all concerned	62 (19.9%)

Table A4. Cont.

Item	Frequency (Percentage)
Q3: Are you concerned that if you use your credit card to buy something on the internet your card will be mischarged?	
Fully concerned	25 (8.0%)
Rather concerned	66 (21.2%)
Neither concerned nor not concerned	71 (22.8%)
Rather not concerned	64 (20.6%)
Not at all concerned	85 (27.3%)
Q4: Are you concerned who might access your medical records electronically?	
Fully concerned	16 (5.1%)
Rather concerned	52 (16.7%)
Neither concerned nor not concerned	73 (23.5%)
Rather not concerned	114 (36.7%)
Not at all concerned	56 (18.0%)

References

- Li, D.; Zhang, R.; Chen, C.; Huang, Y.; Wang, X.; Yang, Q.; Zhu, X.; Zhang, X.; Hao, M.; Shui, L. Developing a Capsule Clinic—A 24-Hour Institution for Improving Primary Health Care Accessibility: Evidence From China. *JMIR Med. Inform.* **2023**, *11*, e41212. [\[CrossRef\]](#)
- Schwamm, L.H. Telehealth: Seven Strategies To Successfully Implement Disruptive Technology And Transform Health Care. *Health Aff.* **2014**, *33*, 200–206. [\[CrossRef\]](#)
- Pool, J.; Akhlaghpour, S.; Fatehi, F.; Gray, L.C. Data Privacy Concerns and Use of Telehealth in the Aged Care Context: An Integrative Review and Research Agenda. *Int. J. Med. Inform.* **2022**, *160*, 104707. [\[CrossRef\]](#)
- Gaziel-Yablowitz, M.; Bates, D.W.; Levine, D.M. Telehealth in US Hospitals: State-Level Reimbursement Policies No Longer Influence Adoption Rates. *Int. J. Med. Inform.* **2021**, *153*, 104540. [\[CrossRef\]](#)
- Massaroni, V.; Delle Donne, V.; Ciccirelli, N.; Ciccullo, A.; Borghetti, A.; Faliero, D.; Visconti, E.; Tamburrini, E.; Di Giambenedetto, S. Use of Telehealth for HIV Care in Italy: Are Doctors and Patients on the Same Page? A Cross-Sectional Study. *Int. J. Med. Inform.* **2021**, *156*, 104616. [\[CrossRef\]](#)
- Reynolds, A.; Awan, N.; Gallagher, P. Physiotherapists' Perspective of Telehealth during the COVID-19 Pandemic. *Int. J. Med. Inform.* **2021**, *156*, 104613. [\[CrossRef\]](#)
- Wang, H.; Liang, L.; Du, C.; Wu, Y. Implementation of Online Hospitals and Factors Influencing the Adoption of Mobile Medical Services in China: Cross-Sectional Survey Study. *JMIR mHealth uHealth* **2021**, *9*, e25960. [\[CrossRef\]](#)
- Sang, L.; Song, L. The Current Status of the Use of Internet Hospitals for Outpatients With Pain: Retrospective Study. *J. Med. Internet Res.* **2023**, *25*, e44759. [\[CrossRef\]](#)
- Liu, L.; Shi, L. Chinese Patients' Intention to Use Different Types of Internet Hospitals: Cross-Sectional Study on Virtual Visits. *J. Med. Internet Res.* **2021**, *23*, e25978. [\[CrossRef\]](#)
- Chen, P.; Xiao, L.; Gou, Z.; Xiang, L.; Zhang, X.; Feng, P. Telehealth Attitudes and Use among Medical Professionals, Medical Students and Patients in China: A Cross-Sectional Survey. *Int. J. Med. Inform.* **2017**, *108*, 13–21. [\[CrossRef\]](#)
- Chen, N.; Liu, P. Assessing Elderly User Preference for Telehealth Solutions in China: Exploratory Quantitative Study. *JMIR mHealth uHealth* **2022**, *10*, e27272. [\[CrossRef\]](#)
- Viney, R.; Lancsar, E.; Louviere, J. Discrete Choice Experiments to Measure Consumer Preferences for Health and Healthcare. *Expert Rev. Pharmacoeconomics Outcomes Res.* **2002**, *2*, 319–326. [\[CrossRef\]](#)
- Cranen, K.; Groothuis-Oudshoorn, C.G.; Vollenbroek-Hutten, M.M.; IJzerman, M.J. Toward Patient-Centered Telerehabilitation Design: Understanding Chronic Pain Patients' Preferences for Web-Based Exercise Telerehabilitation Using a Discrete Choice Experiment. *J. Med. Internet Res.* **2017**, *19*, e26. [\[CrossRef\]](#)
- Kenny, P.; De Abreu Lourenco, R.; Wong, C.Y.; Haas, M.; Goodall, S. Community Preferences in General Practice: Important Factors for Choosing a General Practitioner. *Health Expect.* **2016**, *19*, 26–38. [\[CrossRef\]](#)
- Bridges, J.F.P.; Hauber, A.B.; Marshall, D.; Lloyd, A.; Prosser, L.A.; Regier, D.A.; Johnson, F.R.; Mauskopf, J. Conjoint Analysis Applications in Health—A Checklist: A Report of the ISPOR Good Research Practices for Conjoint Analysis Task Force. *Value Health* **2011**, *14*, 403–413. [\[CrossRef\]](#)
- Reed Johnson, F.; Lancsar, E.; Marshall, D.; Kilambi, V.; Mühlbacher, A.; Regier, D.A.; Bresnahan, B.W.; Kanninen, B.; Bridges, J.F.P. Constructing Experimental Designs for Discrete-Choice Experiments: Report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force. *Value Health* **2013**, *16*, 3–13. [\[CrossRef\]](#)
- Hauber, A.B.; González, J.M.; Groothuis-Oudshoorn, C.G.M.; Prior, T.; Marshall, D.A.; Cunningham, C.; IJzerman, M.J.; Bridges, J.F.P. Statistical Methods for the Analysis of Discrete Choice Experiments: A Report of the ISPOR Conjoint Analysis Good Research Practices Task Force. *Value Health* **2016**, *19*, 300–315. [\[CrossRef\]](#)

18. Deidda, M.; Meleddu, M.; Pulina, M. Potential Users' Preferences towards Cardiac Telemedicine: A Discrete Choice Experiment Investigation in Sardinia. *Health Policy Technol.* **2018**, *7*, 125–130. [\[CrossRef\]](#)
19. Buchanan, J.; Roope, L.S.J.; Morrell, L.; Pouwels, K.B.; Robotham, J.V.; Abel, L.; Crook, D.W.; Peto, T.; Butler, C.C.; Walker, A.S.; et al. Preferences for Medical Consultations from Online Providers: Evidence from a Discrete Choice Experiment in the United Kingdom. *Appl. Health Econ. Health Policy* **2021**, *19*, 521–535. [\[CrossRef\]](#)
20. Chudner, I.; Drach-Zahavy, A.; Karkabi, K. Choosing Video Instead of In-Clinic Consultations in Primary Care in Israel: Discrete Choice Experiment Among Key Stakeholders—Patients, Primary Care Physicians, and Policy Makers. *Value Health* **2019**, *22*, 1187–1196. [\[CrossRef\]](#)
21. von Weinrich, P.; Kong, Q.; Liu, Y. Would You Zoom with Your Doctor? A Discrete Choice Experiment to Identify Patient Preferences for Video and in-Clinic Consultations in German Primary Care. *J. Telemed. Telecare* **2022**. [\[CrossRef\]](#)
22. Mozes, I.; Mossinson, D.; Schilder, H.; Dvir, D.; Baron-Epel, O.; Heymann, A. Patients' Preferences for Telemedicine versus in-Clinic Consultation in Primary Care during the COVID-19 Pandemic. *BMC Prim. Care* **2022**, *23*, 33. [\[CrossRef\]](#)
23. Zhang, Y.; Liu, T.; He, Z.; Chan, S.N.; Huang, J.; Wong, T.-H.; Zhang, C.J.P.; Ming, W.-K. Preferences for Attributes of Initial COVID-19 Diagnosis in the United States and China During the Pandemic: Discrete Choice Experiment With Propensity Score Matching. *JMIR Public Health Surveill.* **2022**, *8*, e37422. [\[CrossRef\]](#)
24. Qureshi, A.A.; Brandling-Bennett, H.A.; Wittenberg, E.; Chen, S.C.; Sober, A.J.; Kvedar, J.C. Willingness-to-Pay Stated Preferences for Telemedicine Versus In-Person Visits in Patients with a History of Psoriasis or Melanoma. *Telemed. e-Health* **2006**, *12*, 639–643. [\[CrossRef\]](#)
25. Snoswell, C.L.; Smith, A.C.; Page, M.; Caffery, L.J. Patient Preferences for Specialist Outpatient Video Consultations: A Discrete Choice Experiment. *J. Telemed. Telecare* **2023**, *29*, 707–715. [\[CrossRef\]](#)
26. Liu, T.; Tsang, W.; Xie, Y.; Tian, K.; Huang, F.; Chen, Y.; Lau, O.; Feng, G.; Du, J.; Chu, B.; et al. Preferences for Artificial Intelligence Clinicians Before and During the COVID-19 Pandemic: Discrete Choice Experiment and Propensity Score Matching Study. *J. Med. Internet Res.* **2021**, *23*, e26997. [\[CrossRef\]](#)
27. Bryan, S.; Dolan, P. Discrete Choice Experiments in Health Economics: For Better or for Worse? *Eur. J. Health Econom.* **2004**, *5*, 199–202. [\[CrossRef\]](#)
28. Hunter, R.F.; Cleland, C.L.; Kee, F.; Longo, A.; Murtagh, B.; Barry, J.; McKeown, G.; Garcia, L. Developing System-Oriented Interventions and Policies to Reduce Car Dependency for Improved Population Health in Belfast: Study Protocol. *Systems* **2021**, *9*, 62. [\[CrossRef\]](#)
29. Clark, M.D.; Determann, D.; Petrou, S.; Moro, D.; De Bekker-Grob, E.W. Discrete Choice Experiments in Health Economics: A Review of the Literature. *Pharmacoeconomics* **2014**, *32*, 883–902. [\[CrossRef\]](#)
30. de Bekker-Grob, E.W.; Ryan, M.; Gerard, K. Discrete Choice Experiments in Health Economics: A Review of the Literature. *Health Econ.* **2012**, *21*, 145–172. [\[CrossRef\]](#)
31. Ryan, M.; Gerard, K.; Amaya-Amaya, M. Discrete Choice Experiments in a Nutshell. In *Using Discrete Choice Experiments to Value Health and Health Care*; Ryan, M., Gerard, K., Amaya-Amaya, M., Bateman, I.J., Eds.; The Economics of Non-Market Goods and Resources; Springer: Dordrecht, The Netherlands, 2008; Volume 11, pp. 13–46. [\[CrossRef\]](#)
32. Soekhai, V.; De Bekker-Grob, E.W.; Ellis, A.R.; Vass, C.M. Discrete Choice Experiments in Health Economics: Past, Present and Future. *Pharmacoeconomics* **2019**, *37*, 201–226. [\[CrossRef\]](#)
33. Viney, R.; Savage, E.; Louviere, J. Empirical Investigation of Experimental Design Properties of Discrete Choice Experiments in Health Care. *Health Econ.* **2005**, *14*, 349–362. [\[CrossRef\]](#)
34. Veldwijk, J.; Lambooij, M.; De Bekker-Grob, E.; Smit, H.; De Wit, G. The Effect of Including an Opt-out Option in Discrete Choice Experiments. *Value Health* **2013**, *16*, A46. [\[CrossRef\]](#)
35. de Bekker-Grob, E.W.; Donkers, B.; Bliemer, M.C.J.; Veldwijk, J.; Swait, J.D. Can Healthcare Choice Be Predicted Using Stated Preference Data? *Soc. Sci. Med.* **2020**, *246*, 112736. [\[CrossRef\]](#)
36. Mühlbacher, A.; Johnson, F.R. Choice Experiments to Quantify Preferences for Health and Healthcare: State of the Practice. *Appl. Health Econ. Health Policy* **2016**, *14*, 253–266. [\[CrossRef\]](#)
37. De Bekker-Grob, E.W.; Donkers, B.; Jonker, M.F.; Stolk, E.A. Sample Size Requirements for Discrete-Choice Experiments in Healthcare: A Practical Guide. *Patient* **2015**, *8*, 373–384. [\[CrossRef\]](#)
38. Blais, A.-R.; Weber, E.U. A Domain-Specific Risk-Taking (DOSPERT) Scale for Adult Populations. *Judgm. Decis. Mak* **2006**, *1*, 33–47. [\[CrossRef\]](#)
39. Buchanan, T.; Paine, C.; Joinson, A.N.; Reips, U. Development of Measures of Online Privacy Concern and Protection for Use on the Internet. *J. Am. Soc. Inf. Sci.* **2007**, *58*, 157–165. [\[CrossRef\]](#)
40. Norman, C.D.; Skinner, H.A. eHEALS: The eHealth Literacy Scale. *J. Med. Internet Res.* **2006**, *8*, e27. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Rahman, M.S.; Ko, M.; Warren, J.; Carpenter, D. Healthcare Technology Self-Efficacy (HTSE) and Its Influence on Individual Attitude: An Empirical Study. *Comput. Hum. Behav.* **2016**, *58*, 12–24. [\[CrossRef\]](#)
42. Wang, Q.; Abihiro, G.A.; Yang, J.; Li, P.; De Allegri, M. Preferences for Long-Term Care Insurance in China: Results from a Discrete Choice Experiment. *Soc. Sci. Med.* **2021**, *281*, 114104. [\[CrossRef\]](#) [\[PubMed\]](#)
43. Oedingen, C.; Bartling, T.; Schrem, H.; Mühlbacher, A.C.; Krauth, C. Public Preferences for the Allocation of Donor Organs for Transplantation: A Discrete Choice Experiment. *Soc. Sci. Med.* **2021**, *287*, 114360. [\[CrossRef\]](#) [\[PubMed\]](#)

44. Nakano, M. Examining Preference for Energy-Related Information through a Choice Experiment. *Energies* **2023**, *16*, 2452. [\[CrossRef\]](#)
45. Dziak, J.J.; Coffman, D.L.; Lanza, S.T.; Li, R.; Jermiin, L.S. Sensitivity and Specificity of Information Criteria. *Brief. Bioinform.* **2020**, *21*, 553–565. [\[CrossRef\]](#)
46. Daly, A.; Dekker, T.; Hess, S. Dummy Coding vs Effects Coding for Categorical Variables: Clarifications and Extensions. *J. Choice Model.* **2016**, *21*, 36–41. [\[CrossRef\]](#)
47. Lancaster, K.J. A New Approach To Consumer Theory. *J. Political Econ.* **1966**, *74*, 132–157. [\[CrossRef\]](#)
48. Savira, F.; Robinson, S.; Toll, K.; Spark, L.; Thomas, E.; Nesbitt, J.; Frean, I.; Norman, R. Consumer Preferences for Telehealth in Australia: A Discrete Choice Experiment. *PLoS ONE* **2023**, *18*, e0283821. [\[CrossRef\]](#)
49. Ebbert, J.O.; Ramar, P.; Tulledge-Scheitel, S.M.; Njeru, J.W.; Rosedahl, J.K.; Roellinger, D.; Philpot, L.M. Patient Preferences for Telehealth Services in a Large Multispecialty Practice. *J. Telemed. Telecare* **2023**, *29*, 298–303. [\[CrossRef\]](#)
50. Rasmussen, B.; Perry, R.; Hickey, M.; Hua, X.; Wong, Z.W.; Guy, L.; Hitch, D.; Hiscock, H.; Dalziel, K.; Winter, N.; et al. Patient Preferences Using Telehealth during the COVID-19 Pandemic in Four Victorian Tertiary Hospital Services. *Intern. Med. J.* **2022**, *52*, 763–769. [\[CrossRef\]](#)
51. Toll, K.; Spark, L.; Neo, B.; Norman, R.; Elliott, S.; Wells, L.; Nesbitt, J.; Frean, I.; Robinson, S. Consumer Preferences, Experiences, and Attitudes towards Telehealth: Qualitative Evidence from Australia. *PLoS ONE* **2022**, *17*, e0273935. [\[CrossRef\]](#)
52. Nanda, M.; Sharma, R. A Review of Patient Satisfaction and Experience with Telemedicine: A Virtual Solution During and Beyond COVID-19 Pandemic. *Telemed. e-Health* **2021**, *27*, 1325–1331. [\[CrossRef\]](#) [\[PubMed\]](#)
53. Watson, A.J.; Bergman, H.; Williams, C.M.; Kvedar, J.C. A Randomized Trial to Evaluate the Efficacy of Online Follow-up Visits in the Management of Acne. *Arch. Dermatol.* **2010**, *146*, 406–411. [\[CrossRef\]](#) [\[PubMed\]](#)
54. Hertzog, R.; Johnson, J.; Smith, J.; McStay, F.W.; Da Graca, B.; Haneke, T.; Heavener, T.; Couchman, G.R. Diagnostic Accuracy in Primary Care E-Visits: Evaluation of a Large Integrated Health Care Delivery System's Experience. *Mayo Clin. Proc.* **2019**, *94*, 976–984. [\[CrossRef\]](#) [\[PubMed\]](#)
55. Shigekawa, E.; Fix, M.; Corbett, G.; Roby, D.H.; Coffman, J. The Current State Of Telehealth Evidence: A Rapid Review. *Health Aff.* **2018**, *37*, 1975–1982. [\[CrossRef\]](#)

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