



Using machine learning to explore the determinants of service satisfaction with online healthcare platforms during the COVID-19 pandemic

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Abstract

This study investigates the determinants of service satisfaction with online healthcare platforms using machine learning (ML) algorithms. By training and testing eleven ML models based on data mined from a leading online healthcare platform in China, we obtained the best-performing ML algorithm for service satisfaction prediction, namely, Light Gradient Boosting Machine. Furthermore, our empirical results indicate that gifts, patient votes, popularity, fee-based consultation volume, gender, and thank-you letters positively impact service satisfaction, while the impacts of consultation volume, free consultation volume, views, waiting time, articles, physician title, and hospital level are negative. We discuss the theoretical and managerial implications.

Keywords Service satisfaction · Machine learning · Online healthcare platforms · COVID-19

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1 Introduction

During the worldwide outbreak of the epidemic (COVID-19), online healthcare platforms, as one of the most essential smart and connected healthcare applications, played an important role in telehealth and telemedicine consultations between patients and physicians (Liu et al. 2022b). Compared with traditional in-person office visits, these platforms remove the restrictions of time and space, thus decreasing in-person hospital visits. In addition, because there is no in-person contact, the platforms also decrease the risk of spreading diseases such as COVID-19 (Asllani and Trimi 2022; Guo et al. 2016). Moreover, because patients trust their online search more, no longer simply relying on physicians' advice, online healthcare platforms have become more attractive to patients (Lee and Lee 2022). Online healthcare platforms allow patients to communicate conveniently with physicians via text or voice interaction. In turn, physicians can answer patients' problems on the Internet anytime and anywhere, so online healthcare platforms provide a place for physician–patient communication (Chen et al. 2022a).

Indeed, service satisfaction with online healthcare platforms is a metric with significant meaning for patients and physicians using online healthcare platforms that influences healthcare service providers and society in general. On online healthcare platforms, service satisfaction is an essential indicator of the quality of healthcare services and reflects users' perceptions and attitudes toward their total healthcare experience (Lu et al. 2021b; Prakash 2010). Service satisfaction with online healthcare platforms is becoming a vital component of service quality improvement and clinical efficacy, which suggests a need for routine studies to improve the existing quality evaluation methods and ensure the smooth functioning of the healthcare system (Asamrew et al. 2020; Isenberg and Stewart 1988). For these reasons, identifying the drivers of service satisfaction with online healthcare platforms is critical to revolutionizing smart health and well-being applications.

Researchers have used various perspectives to broadly investigate service satisfaction as a determinant of the value co-creation process with online healthcare platforms (e.g., Bertakis et al. 1991; Lee 2019; Liu et al. 2020; Lou et al. 2022; Wu and Lu 2018; Yang et al. 2015). However, the COVID-19 crisis has vastly accelerated the global demand and development of online healthcare. First, COVID-19 is a contagious respiratory illness characterized by severe virulence, which has intensified the existing shortage of medical resources (Ba and Wang 2013). At the beginning of the COVID-19 pandemic in China, physical hospitals and other traditional healthcare systems failed to provide adequate services for patients infected with COVID-19 and other diseases (Sun et al. 2021). Moreover, strict social containment measures, such as social distancing, restricted most patients from accessing traditional face-to-face services (Lee and Lee 2021). Consequently, telemedicine on online healthcare platforms, as a smart connection between patients and physicians, has become increasingly popular as an alternative to traditional healthcare services. Therefore, we need a more nuanced investigation of service satisfaction drivers in the context of the continuing COVID-19 pandemic.

In our study, we used a machine learning approach to investigate service satisfaction, which as an advanced methodology, overcomes the shortcomings of conventional techniques. Several biases (e.g., common method bias, non-response bias, and sample selection bias) may exist in survey-based research and influence the validity and accuracy in determining service satisfaction (Clottey and Grawe 2014; Min et al. 2016; Rönkkö et al. 2016). However, because online healthcare platforms generate a large volume of complex data, it makes sense to select machine learning techniques to explore the mechanism of contactless healthcare services (Qayyum et al. 2020). Furthermore, as cloud computing and big data technology improve by leaps and bounds, we can apply machine learning in the health field to improve the accuracy of predicted outcomes and human-centered intelligent solutions, enabling better healthcare service (Chen and Lin 2014). Notably, the prediction results generated from machine learning models are robust and replicable in different samples from the same population (Shrestha et al. 2021). Such characteristics help us to overcome prediction errors that may arise from sampling errors. This study uses machine learning to explore the determinants of service satisfaction from three perspectives: physician characteristics, interaction characteristics, and consultation volume. Specifically, we put forward three research questions (RQs).

- RQ1 How do physician characteristics (e.g., gender, physician title, hospital level, articles) affect service satisfaction?
- RQ2 How do interaction characteristics (e.g., views, patient votes, thank-you letters, gifts, popularity, waiting time) affect service satisfaction?
- RQ3 How does consultation volume (e.g., consultation volume, fee-based consultation volume, free consultation volume) affect service satisfaction?

To answer these questions, we collected a large-scale dataset during the COVID-19 era from a leading Chinese online healthcare platform and used machine learning algorithms to predict service satisfaction. Our study provides three contributions to the online healthcare field. First, we offer an effective predictive model for determining service satisfaction with online healthcare platforms using a machine learning approach—a response to a call for papers using health data processing and analytics methods to discover new insights. Machine learning algorithms fit the data better and predict more accurately than traditional regression models (Dvir et al. 2006). Applying artificial intelligence has thus been a hot issue in the healthcare industry in current research. Our results indicate that the Light Gradient Boosting Machine (LightGBM) is the most accurate predictor. Second, this study examined service satisfaction with online healthcare platforms by evaluating physician characteristics, interaction characteristics, and consultation volume. The results indicate that consultation volume is the most critical determinant, followed by free consultation volume, gifts, patient votes, views, waiting time, popularity, fee-based consultation volume, gender, thank-you letters, articles, physician title, and

hospital level. Physicians and online healthcare platforms could use our findings as a reference for a better understanding of online health service and physician–patient relationships. Third, this study adds significant knowledge by exploring service satisfaction during COVID-19. The COVID-19 pandemic forced patients to prioritize remote healthcare services over face-to-face consultations. Our study provides novel findings that one could use to design a better online health system in this context. Overall, this study offers insights into online healthcare service management and can aid platform managers in improving the design of smart and connected health systems. Collectively, these findings extend the knowledge in the health field and provide a train of thought for further studies of online healthcare platforms.

This study is structured as follows. Section 2 is the literature review, Sect. 3 presents the data and methods, and Sect. 3.4 describes our results and analyses. Then, Sect. 4 discusses the study’s theoretical and practical implications, and finally, Sect. 5 summarizes the study and concludes.

2 Literature review

As an essential metric for consumer management, service satisfaction with online healthcare platforms plays an important role and has been researched many times in previous literature (Lee and Lee 2022; Liu et al. 2019). On online healthcare platforms, service satisfaction is the degree to which patients feel satisfied with the health services provided by the physician and the gap between expected and perceived characteristics (Raposo et al. 2009), which represents a patient’s psychological state after a physician has completed consultation (Yang et al. 2019). From the online healthcare perspective, service satisfaction can be defined as the cognition and general evaluation of the online healthcare service quality (Lu et al. 2021b; Prakash 2010). This study primarily builds on five streams: (1) one stream describes the development of the online healthcare platform, (2) the second stream is on detecting the effects of physician characteristics on service satisfaction, (3) the third stream investigates the relationship between interaction characteristics and service satisfaction, (4) the fourth stream examines how consultation volume influences service satisfaction, and (5) the last stream reviews the function and value of machine learning in the healthcare industry.

2.1 The development of online healthcare platforms

Online healthcare platforms are websites that provide online health services for healthcare and consultation using information technology (Jiang et al. 2021). Patients, physicians, medical staff, and other stakeholders use these platforms to communicate and share healthcare information (Guo et al. 2016). Compared to traditional health service modes, it optimizes the utilization of medical resources and simplifies the patient care process, providing communication between patients and physicians (Ding et al. 2022; Guo et al. 2016). Owing to limited and unevenly

distributed medical resources, and the outbreak of the COVID-19 epidemic, online healthcare platforms are in huge demand (Jiang et al. 2021). In China, for instance, there were only 2.77 licensed physicians per 1000 people in 2019, dropping to 1.96 for rural residents (Jiang et al. 2021). Additionally, in the United States, 59% of American adults have searched for relevant health information, and 35% have looked for medical solutions for someone with a disease (Zhang et al. 2018). Online health platforms, however, can help alleviate the burden on medical resources and, to some extent, solve such problems (Guo et al. 2016). Previous studies indicated that online healthcare platforms allow treated patients to share experiences and obtain health information quickly, extensively aiding patients during COVID-19 (e.g., Fan et al. 2014; Liu et al. 2022b; Zhang et al. 2018; Zhao et al. 2015). For instance, Jiang et al. (2021) reported a dramatic increase in online consultations in China during the pandemic, which alleviated the unavailability of healthcare resources due to the lockdown, allowing online healthcare platforms to play a key role in defending against COVID-19, such as healthcare information sharing, providing prescriptions, and arranging drug delivery. With this in mind, we believe it is necessary to investigate in depth the factors influencing satisfaction with online healthcare platforms.

2.2 Physician characteristics

Researchers widely acknowledge the significance of physician characteristics in service satisfaction (El-Nassir and Mohammed 2013). For example, a physician's gender is one of the most obvious difference that makes a discrepant impression on patients. Female physicians must cater to patients' stereotypes, as they expect to receive more empathy and care from female physicians (Bertakis et al. 1991). However, male physicians operate in more space and face fewer limitations (Michael et al. 1991). On online healthcare platforms, the number of articles, as a symbol of a physician's level of activity and effort, can attract patients to browse (Li et al. 2019d). In prior literature, patients found physicians with higher titles and hospital levels more appealing, which caused an uneven distribution of medical resources (Hsu et al. 2022). In other words, even if there is no significant difference in physician quality, patients are unwilling to choose lower-level physicians (Liu et al. 2020). Thus, high hospital level physicians draw more patients, positively affecting service satisfaction (Guo et al. 2017). Furthermore, physicians' response speed affects service satisfaction and has been a vital topic among scholars (Yang et al. 2015). Accordingly, physician characteristics play a critical role in enhancing service satisfaction.

2.3 Interaction characteristics

In contrast to physician characteristics, interaction characteristics are a more direct route for delivering service satisfaction. It refers to the information exchange among the community members and between the members and the community hosts (Jang et al. 2008). In the context of our study, interaction characteristics mainly include

virtual gifts, thank-you letters, etc., which change healthcare processes and outcomes (Shmargad and Watts 2016; Wang et al. 2020). As an expression of gratitude, gifts always positively affect physician consultations. However, if patients pay high consultation fees, physicians may receive fewer gifts, negatively influencing service satisfaction (Wang et al. 2020). In addition, thank-you letters are vital to service satisfaction, a crucial parameter for interaction characteristics (Herbland et al. 2017). Similar to views and patient votes, they express the same appreciation for physicians, but patients can deliver thank-you letters by hand to make the gesture seem more direct and personal (Miron-Shatz et al. 2017). Waiting time has already been recognized as related to a physician's earnings (Gupta and Denton 2008), implying that it plays a vital role in online health platforms. Intuitively, improving waiting time will lead to tangible improvements in service satisfaction, but prior literature has revealed that the magnitude of the effect of waiting time varies across specialties (Ko et al. 2019). Overall, interaction characteristics may result in a series of improvements that affect service satisfaction from various perspectives.

2.4 Consultation volume

The number and price of consultations are closely related to service satisfaction (Liu et al. 2019). Before the availability of online consultations, previous literature found no significant difference in service satisfaction between telephone consultations and face-to-face consultations (McKinstry et al. 2002). However, due to the popularity of online healthcare platforms, online consultation volume plays a crucial part in service satisfaction. As a sign of quality, the price of consultations affects the economics of online healthcare platforms (Liu et al. 2019). Interestingly, some scholars have proposed that although free consultations generate no income, they may generate paid consultations in the future (Li et al. 2019a). Meanwhile, free consultations could increase patients' certainty in service quality and promote the demand for fee-based consultation and the returns of health service providers (Hu 2019). By increasing the price of consultations, patients consider that they can receive better service quality and service satisfaction (Wu and Lu 2018) due to the high demand for a physician's services (Gerstner 1985). Finally, we believe that studying consultation volume can advance the understanding of service satisfaction and improve the operation of online healthcare platforms.

2.5 Machine learning in the healthcare industry

The healthcare industry widely uses machine learning, a main and essential branch of artificial intelligence (Kononenko 2001). This technique simulates human behaviors to identify and obtain information and knowledge using computers based on original knowledge and information, to upgrade and improve some abilities of businesses (Portugal et al. 2018). By training models with extra knowledge, machine learning is a suitable methodology to analyze and interpret a large-scale dataset to achieve precise results and reliable conclusions. This approach is superior to traditional methods in predicting operational performance and diseases, identifying

and labeling images, and has a decision-making capability over data (Sabahi and Parast 2020; Wang et al. 2011).

Using machine learning algorithms can make disease predictions, aid medical diagnoses, support healthcare decision-making, and improve patient experiences, thereby delivering transformational performance in the healthcare industry. For example, in medical technology related to cancer, researchers use machine learning techniques, including neural trees, Bayesian networks, and radial basis function (RBF) networks, to classify cancer types by revealing the relationship between genes to improve essential genes for cancer classification (Hwang et al. 2002; Zhang et al. 2022). In addition, machine learning can make full use of resources in healthcare and cut the medical cost to advance patient care (Tucker et al. 2020). Machine learning is an effective way to direct patients to receive optional treatment, helping physicians formulate a suitable treatment plan and keep costs down by improving medical efficiency, demonstrating the importance of machine learning in the healthcare industry (Chen et al. 2019; Waring et al. 2020).

Compared with the existing literature, this study conducts machine learning to investigate a vital target in the healthcare industry: service satisfaction with online healthcare platforms. Specifically, the current research explores how the compound influencing factors of physician characteristics, interaction characteristics, and consultation volume affect service satisfaction with online healthcare platforms in the context of the COVID-19 pandemic. By building machine learning models that determine service satisfaction, this study identifies the importance of the various feature variables and examines the determinants of service satisfaction with online healthcare platforms.

3 Data and methods

3.1 Data acquisition and processing

We collected data from Good Physician Online (<https://www.haodf.com/>), one of China's largest online health communities. The platform was founded in 2006, and as of July 2022, it has over 10,000 hospitals and 890,000 registered physicians. The platform processes diversified functions such as gift-giving, online consultations, and knowledge dissemination (Chen et al. 2020). We selected this site for the following reasons: (1) it gathers the most abundant and comprehensive data and is one of the most authoritative online platforms, and (2) the relationships between the platform and physicians are cooperative but independent. This feature ensures that data from the site about physicians are pertinent and verifiable; thus, physicians have no reason to endorse false information on behalf of the platform. The platform allows patients to gather knowledge about a specific physician and consult with them about their health problems. Every physician has a homepage, which exhibits their basic information and details their achievements, including articles, thank-you letters, gifts, etc. The homepage is the portal for mutual communication and, in the interaction process, is a determinant of patients choosing a suitable physician.

Table 1 Variable descriptions

Variable	Measures
Service satisfaction	Ln (the percentage of positive comments in online service evaluation)
Physician characteristics	
Gender	0 = male, 1 = female
Physician title	1 = resident physician, 2 = attending physician, 3 = deputy chief physician, 4 = chief physician
Hospital level	1 = first-level grade-B, 2 = first-level grade-A, 3 = second-level grade-B, 4 = second-level grade-A, 5 = third-level grade-B, 6 = third-level grade-A
Articles	The number of articles written by a physician
Interaction characteristics	
Patient votes	The number of votes from patients
Thank-you letters	The number of thank-you letters from patients
Views	Ln (the number of the online patient visits)
Gifts	The number of gifts received from patients
Popularity	Patients' recommendations for a physician
Waiting time	The time spent waiting for a physician; 1 is the shortest and 5 is the longest
Consultation volume	
Consultation volume	Ln (the number of online consultations plus 1)
Fee-based consultation volume	Ln (the number of fee-based services offered by a physician plus 1)
Free consultation volume	Ln (the number of free services offered by a physician plus 1)

We collected information on 234,038 physicians (e.g., physician characteristics, interaction characteristics, etc.) and 1,048,567 orders (i.e., whether there was a charge for the order) for the full year of 2020. Subsequently, because the dependent variable we investigate is service satisfaction, we retained the data containing service satisfaction, aggregating to 7999 pieces of data. Meanwhile, to enhance the explanatory power of our data, we deleted the variables unrelated to the dependent variable. Lastly, we incorporated treated physician information with order information according to physicians' numbers to yield the final dataset.

3.2 Variables

In this study, service satisfaction is the dependent variable, measured by the percentage of positive ratings in online service evaluations (Yang et al. 2015). Positive ratings reflect a patient's satisfaction with a physician's treatment, and thus, we use the percentage of positive ratings as a proxy for patient satisfaction with service quality. To reduce skewness in the distribution, we used the natural logarithm of service satisfaction.

Table 1 shows the details of our feature variables, including gender, physician title, hospital level, articles, patient votes, thank-you letters, views, gifts, popularity, waiting time, consultation volume, and fee-based and free consultation volumes,

Table 2 Descriptive statistics of the variables

Category	Variable	Mean	Std	Min	Max
Physician characteristics	Service satisfaction	4.58	0.06	4.09	4.61
	Gender	0.38	0.49	1.00	1.00
	Articles	48.66	985.96	0.00	86871.00
	Physician title	3.14	0.84	1.00	4.00
Interaction characteristics	Hospital level	5.89	0.45	1.00	6.00
	Gifts	220.17	425.20	0.00	6291.00
	Patient votes	194.69	281.73	0.00	4057.00
	Views	13.20	1.87	4.01	19.06
	Waiting time	1.78	1.16	1.00	5.00
Consultation volume	Popularity	3.87	0.57	2.40	5.00
	Thank-you letters	93.53	142.38	0.00	1987.00
	Consultation volume	7.25	1.39	0.69	11.25
	Free consultation volume	3.14	1.14	0.00	8.072
	Fee-based consultation volume	1.66	1.47	0.00	7.711

Table 3 An overview of frequency analysis of categorical and ordinal variables

Main categories	Sub-categories	Frequency (percent)
Gender	Male	4937 (62%)
	Female	3062 (38%)
Physician title	Resident physician	223 (2.79%)
	Attending physician	1656 (20.70%)
	Deputy chief physician	2915 (36.44%)
	Chief physician	3205 (40.07%)
Hospital level	First-level grade-B	16 (0.20%)
	First-level grade-A	1 (0.01%)
	Second-level grade-B	51 (0.64%)
	Second-level grade-A	116 (1.45%)
	Third-level grade-B	385 (4.81%)
	Third-level grade-A	7430 (92.89%)

following existing studies (e.g., Hu 2019; Li et al. 2019c; Ko et al. 2019; Wang et al. 2020;). In addition, we present the descriptive statistics of all variables in Table 2. Among them, gender is a categorical variable and physician title and hospital level are the ordinal variables. Their specific frequency and percentage are shown in Table 3. Gender is a binary variable that takes the value of 1 if the physician is female; otherwise, it is 0. 38% are female, and 62% are male. Physician title is a performance of a physician's seniority and ranges from 1 to 4 representing *resident physicians*, *attending physicians*, *deputy chief physicians*, and *chief physicians*, respectively. Specifically, chief physicians account for the largest proportion of the total sample (40.07%), followed by deputy chief physicians (36.44%), attending

physicians (20.70%), and resident physicians (2.79%). We measured hospital level on a scale of 1 (lowest) to 6 (highest); level 6 (i.e., Third-level grade-A) accounted for more than 90% of all hospitals, with the remaining 10% including all other levels. Articles are important from physicians' perspectives, and patient votes, thank-you letters, views, and gifts are expressions of patients' appreciation. We used the natural logarithm of views as an individual feature with all other features remaining in their original form. Popularity represents the overall recommendation rating of patients about physicians (Liu et al. 2022a). Moreover, the time a patient spends waiting for a physician before their consultation is the waiting time. As it is important in determining a physician's quality, we divided waiting time into five levels from 1 (fastest) to 5 (slowest). Consultation volume includes total, fee-based, and free consultation volumes—we used the natural logarithm of the number of their values plus 1 to enhance our model's accuracy.

3.3 Machine learning methodology

According to pattern recognition and computational learning theories, machine learning can capture crucial information from existing data and use it to forecast (Young and Chiou 2018). This approach yields a more accurate and consistent evaluation, thus simplifying our prediction process (Bertsimas et al. 2021). There are two types of machine learning methodology: individual machine learning and ensemble machine learning. We draw upon five individual machine learning methods (Ridge, Lasso, Elastic net, Decision tree) and seven ensemble machine learning methods (Bagging, Random forest, Extra tree, AdaBoost, GBDT, XGBoost, LightGBM). An ensemble machine learning method, bagging is the earliest EML algorithm (Breiman 1996) that one can use to select different datasets that replace the existing datasets to obtain diverse conclusions. Consistent with bagging, random forest uses a more complex construction of the original decision tree (Wang and Ma 2012), which results in more effective and accurate predictions (Fawagreh et al. 2014). XGBoost improves its scalability in all states owing to its systems and algorithms. The innovation of its algorithm derives from its use of a new tree learning algorithm for processing sparse data and distributed computing to accelerate the learning speed, thus more easily extending the models. As proof of its superiority, researchers have used XGBoost in billions of cases while using fewer resources than alternative methods (Chen and Guestrin 2016). The advantage of LightGBM, another valuable model, lies in its reduced calculation time regarding rows and columns because it bundles mutually exclusive features. Moreover, LightGBM uses leaf-wise (i.e., best-first) growth (Friedman et al. 2000), which, unlike XGBoost, uses a level-wise strategy, indiscriminately splitting the leaf nodes.

We used SHapley additive exPlanations (SHAP) to improve model interpretability to exhibit how the model's features influence service satisfaction. SHAP interprets predictions by assigning a shape value to features with specific attributes as follows: (1) the interpretation model must match the output of the primary model to prove the local accuracy, (2) the missing features should have no influence on the original input, and (3) when the model depends more on some features, the researcher must

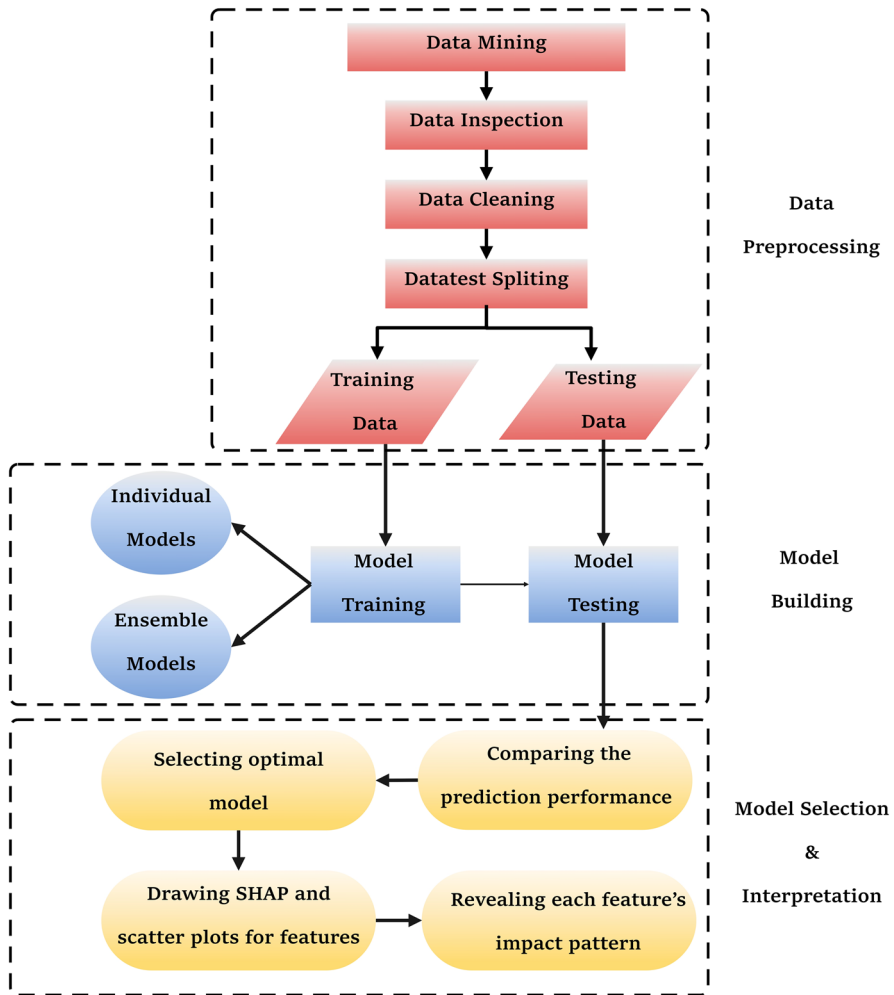


Fig. 1 Flow chart of the analytical framework

not reduce the importance of those features, regardless of all other features. Due to those properties, SHAP fits more with human intuition than alternative methods (Antwarg et al. 2021). Through a novel interpretable model based on machine learning techniques and SHAP, this study identified the importance of each predictor of service satisfaction.

3.4 Research framework

Figure 1 shows the general research framework, a detailed explanation of which follows. The first step is data processing. In the mined data, there are several missing and disordered values. Therefore, cleaning and processing the data before

embedding them into the model is essential. After doing so, we randomly split the data into a training set (80%) and a test set (20%).

We conducted individual and ensemble machine learning methods to analyze the data in the model-building step. Moreover, the most significant step in machine learning is understanding the splitting configuration for estimation and hyperparameter tuning. By applying GridSearchCV (i.e., an exhaustive parameter search algorithm), we obtained the parameters corresponding to the estimated model features and the optimal hyperparameter combination (Lu et al. 2021a). In setting the optimal hyperparameters for the different models, each model produced optimized results; we compared the results of each using mean squared error (MSE) and R-squared (R^2), two types of variables that measure the performance of each model.

The final step is model selection and interpretation. After model testing and hyperparameter optimization, we compared the fitting performance of each model using MSE and R^2 and then selected the most accurate model. In the next step, by drawing SHAP summary plots, we obtained the feature attribution information of each instance in the optimal model. Such attribution information can help examine the models' fitting performance. The model sorts all features in descending order according to their general attribution to the model results through the SHAP summary plots. Next, we selected the optimal model with all of features for our analysis. Lastly, we drew the SHAP dependence and scatters plots including all features, to investigate how they influence the dependent variable.

4 Results

4.1 Performance comparison

We used two metrics to measure and compare the prediction performance of the machine learning algorithms—MSE and R^2 (Balaji et al. 2021). MSE is an index used to evaluate the degree of variation in a prediction model, where a smaller MSE corresponds to better performance. Unlike previous studies that solely relied on MSE to assess algorithm performance (e.g., Antwarg et al. 2021; Sabahi and Parast 2020), this study also considers another critical metric, R^2 , as a performance indicator. R^2 is an effective index that states the degree to which the model directly explains the dataset; its superiority lies in normalizing the results, thus revealing the differences between the models. Algorithms with lower MSE and higher R^2 are considered to have better predictive performance. Equations (1) and (2) show the formulas for these metrics.

$$MSE = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - \hat{y})^2 \quad (1)$$

Table 4 The performance comparison of machine learning algorithms

Methods	MSE	R ²
LightGBM	0.00287	0.06165
XGBoost	0.00289	0.03261
Random forest	0.00294	0.03324
Extra tree	0.00294	0.03323
GBDT	0.00294	0.03259
Lasso	0.00297	0.03398
Elastic net	0.00299	0.03401
Bagging	0.00306	0.03424
Ridge	0.00310	0.03406
AdaBoost	0.00326	0.02253
Decision tree	0.00628	0.03829

$$R^2 = \frac{\sum_{i=1}^N (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2}, \quad (2)$$

where y_i is the i th observed label value, \hat{y}_i is the i th predicted service satisfaction, \bar{y} is the service satisfaction, and N is the total number of instances in the dataset.

Table 4 shows that LightGBM reported the lowest MSE which is 0.00287, followed by XGBoost (MSE=0.00289), Random forest (MSE=0.00294), Extra tree (MSE=0.00294), and GBDT (MSE=0.00294), whereas Decision tree (MSE=0.00628) turned in the worst algorithm performance. In general, the MSE in our models concentrates at about 0.003. Comparing to other models, LightGBM is the most accurate model to predict service satisfaction through our dataset. In addition, in descending order of R^2 , LightGBM ($R^2=0.06165$) has a better predictive performance than other algorithms, followed by Decision tree ($R^2=0.03829$) and Bagging ($R^2=0.03424$). Most methods' R^2 values range from 0.032 to 0.039, which implies that those methods capture about 3% to 4% of variance from the dataset, but AdaBoost only captures 2% of the variance and thus has the lowest effect. So the R^2 of LightGBM is higher than in other models, demonstrating a better fit for our data. In conclusion, LightGBM is the optimal model for our dataset, as it has the lowest MSE and highest R^2 . Therefore, we have reason to conclude that the SHAP interpretation for LightGBM is the most accurate for our dataset.

4.2 Model interpretability

According to our analysis, LightGBM is the best model for predicting service satisfaction using our dataset. We can separate LightGBM into feature parallelism, data parallelism, and voting parallelism. We apply feature parallelism when there are many features of a situation. When there are numerous datasets, we use data parallelism. Finally, voting parallelism is more suitable when there are many features and votes (Ma et al. 2018). LightGBM splits the nodes by leaf splitting, and

its computational costs are relatively small compared to other ensemble machine learning methods. Thus, we must control the data used for each leaf node and tree depth to avoid the occurrence of the fitting phenomenon.

We draw SHAP summary plots based on the LightGBM model to validate the model and obtain the influential factors. SHAP is a unified framework that assists scholars in interpreting the predictions of complex models (Lundberg and Lee 2017). SHAP produces excellent theoretical results, which is beneficial in regulated scenarios. Its values quantify the contribution of each feature variable and validate their relationship with the dependent variable (Lundberg and Lee 2017). According to the literature, we can calculate the SHAP values as follows:

$$SHAPvalue_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(M - |S| - 1)!}{M!} [f_x(S \cup \{i\}) - f_x(S)], \quad (3)$$

where i is an input feature, N is the set of all input features, M is the number of all input features, and S is a subset of N , of which the number of input features is $|S|$. f_x delegates the predicted value of data instances in our models. $f_x(S)$ is the predicted value using the set of features S on data instances, and $f_x(S \cup \{i\})$ represents the predicted value using the set of features S plus feature i .

Figures 2 and 3 illustrate the SHAP values of each feature described by the SHAP value plots. By comparing the SHAP values of different features, it is possible to identify each feature's contribution and thus estimate its influence on the dependent variable. Figure 2 plots the SHAP values for a feature variable on a row, and the color shows whether an instance is positive (red), negative (blue), or neutral (purple) for each observation. In addition, the figures show the order of the feature importance, ranked from high to low: consultation volume, free consultation volume, gifts, patient votes, views, waiting time, popularity, fee-based consultation volume, gender, thank-you letters, articles, physician title, and hospital level.

To explore each feature's impact through their SHAP values, Fig. 3 shows a straightforward SHAP plot, where red indicates a positive effect and blue a negative effect. The figure also demonstrates that consultation volume, free consultation volume, views, waiting time, articles, physician title, and hospital level negatively impact service satisfaction. By contrast, gifts, patient votes, popularity, fee-based consultation volume, gender, and thank-you letters positively affect service satisfaction.

Table 5 indicates the influence on service satisfaction based on physician characteristics, interaction characteristics, and consultation volume. First, the SHAP values of physician characteristics range from 0.00002 to 0.0015, meaning these variables are relatively less essential to service satisfaction than the other perspectives (RQ1). Due to these results, we can speculate that when patients select physicians, the patient will focus less on gender, articles, physician title, and hospital level. Unlike in-person consultation, it's hard to communicate medical advice through online healthcare platforms (Almathami et al. 2022). Hence, patients may not be sensitive to physician characteristics but pay more attention to service quality than to judging service satisfaction (Lu and Wu 2016). So, physician characteristics play a minor role in affecting service satisfaction generally. Specifically,

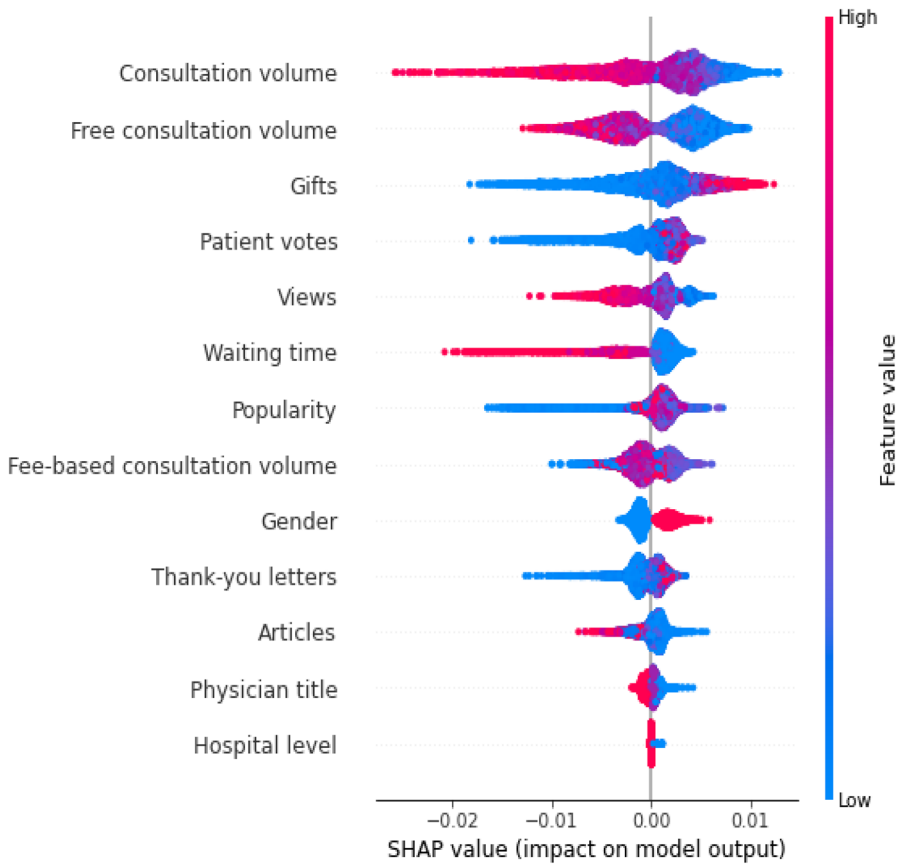


Fig. 2 SHAP summary plots for the LightGBM model

female physicians are more likely to receive better patient service satisfaction ($b=0.92112$). In addition, higher physician titles ($b=-0.85943$) and hospital levels ($b=-0.41331$) are associated with poorer service satisfaction. Further, the number of articles ($b=-0.06474$) has a minor and negative effect on service satisfaction.

Figure 4 illustrates that when the value of gender is 1 (i.e., a physician is female), the SHAP value presented by the plot is significantly higher than the SHAP value when the value of gender is 0 (i.e., a physician is male). Thus, we can infer that male physicians generally obtain less service satisfaction than female physicians. Moreover, when the number of articles is less than 2,000, the value of service satisfaction scatters over a vast span. We believe there is no regularity in articles' influences on service satisfaction, which means patients regard articles as a trivial variable for service satisfaction. Besides, physician title and hospital level are similar to SHAP values, 0.00060 and 0.00002. Figure 4 indicates that the SHAP value decreases as physician title and hospital level increase. Service satisfaction is the best when the physician title is 2, and the hospital level is 4. However, as they

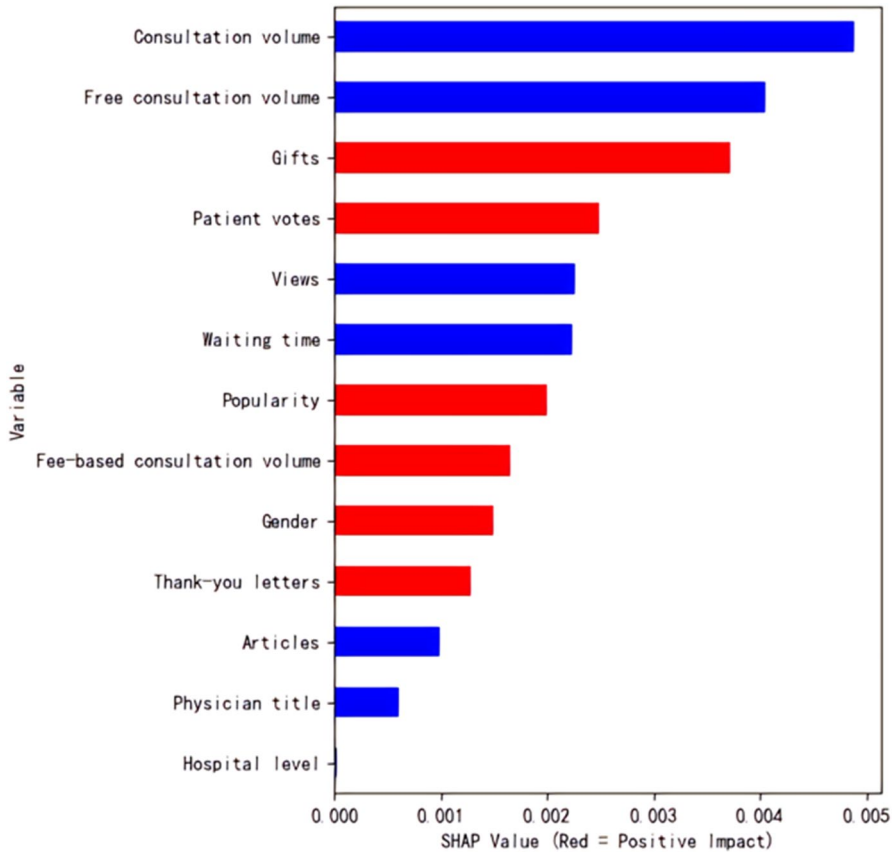


Fig. 3 Summary of SHAP values for the determinants of service satisfaction

continue to increase, service satisfaction reaches the lowest, illustrating that patients may not consider physician title and hospital level as essential criteria to determine service satisfaction when physician title and hospital level are the highest, which is consistent with the findings of Ren and Ma (2021).

Second, the interaction characteristics play a positive role, and variables in interaction characteristics have different levels of influence (RQ2). The detailed contents of interaction characteristics represent that patients receive treatment and reflect on the physician's service in this treatment. If patients show positive interaction characteristics such as many thank-you letters, patient votes, and so on, it can indicate that this physician solves health problems or provides high-quality service, and patients are satisfied with the service (Zhou et al. 2022). Gifts ($b=0.55910$) generate the strongest positive impact on service satisfaction. The next is patient votes, whose effect on service satisfaction is 0.43750. In addition, popularity ($b=0.40770$) and thank-you letters ($b=0.40760$) have similar abilities to influence service satisfaction positively. The remaining variables, views and waiting time, negatively affect service satisfaction. Comparatively, the negative effect of

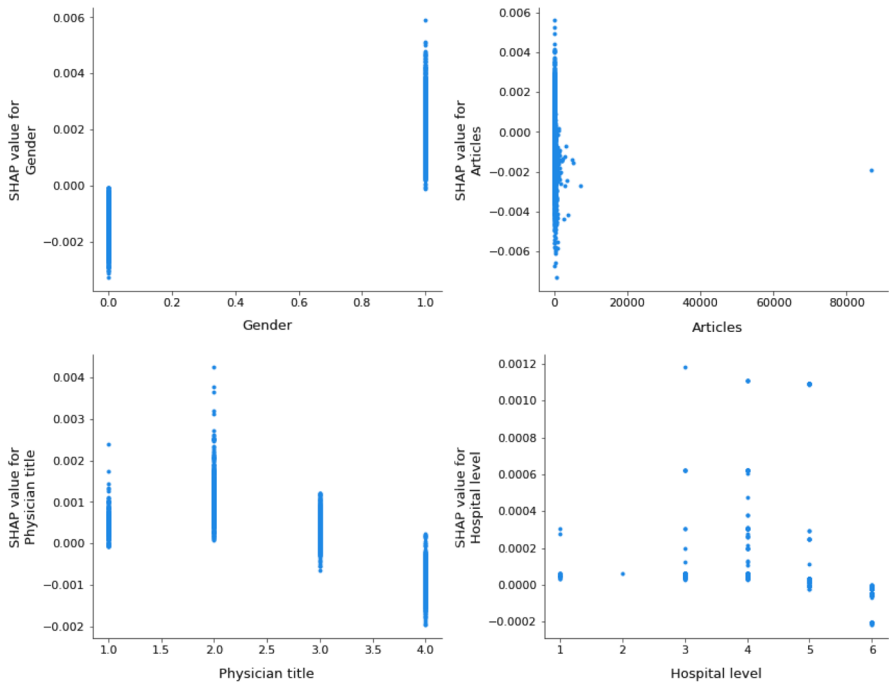


Fig. 4 Dependence plots for physician characteristics

waiting time ($b = -0.86540$) is stronger than views ($b = -0.83690$) to a certain degree.

Table 5 The SHAP values of the determinants of service satisfaction

Category	Variable	Absolute SHAP value	Effects	Sign
Physician characteristics	Gender	0.00149	0.92112	Positive
	Articles	0.00099	-0.06474	Negative
	Physician title	0.00060	-0.85943	Negative
	Hospital level	0.00002	-0.41331	Negative
Interaction characteristics	Gifts	0.00372	0.55910	Positive
	Patient votes	0.00249	0.43750	Positive
	Views	0.00226	-0.83690	Negative
	Waiting time	0.00224	-0.86540	Negative
	Popularity	0.00200	0.40770	Positive
	Thank-you letters	0.00128	0.40760	Positive
	Consultation volume	Consultation volume	0.00489	-0.86980
Free consultation volume		0.00405	-0.82730	Negative
Fee-based consultation volume		0.00165	0.01980	Positive

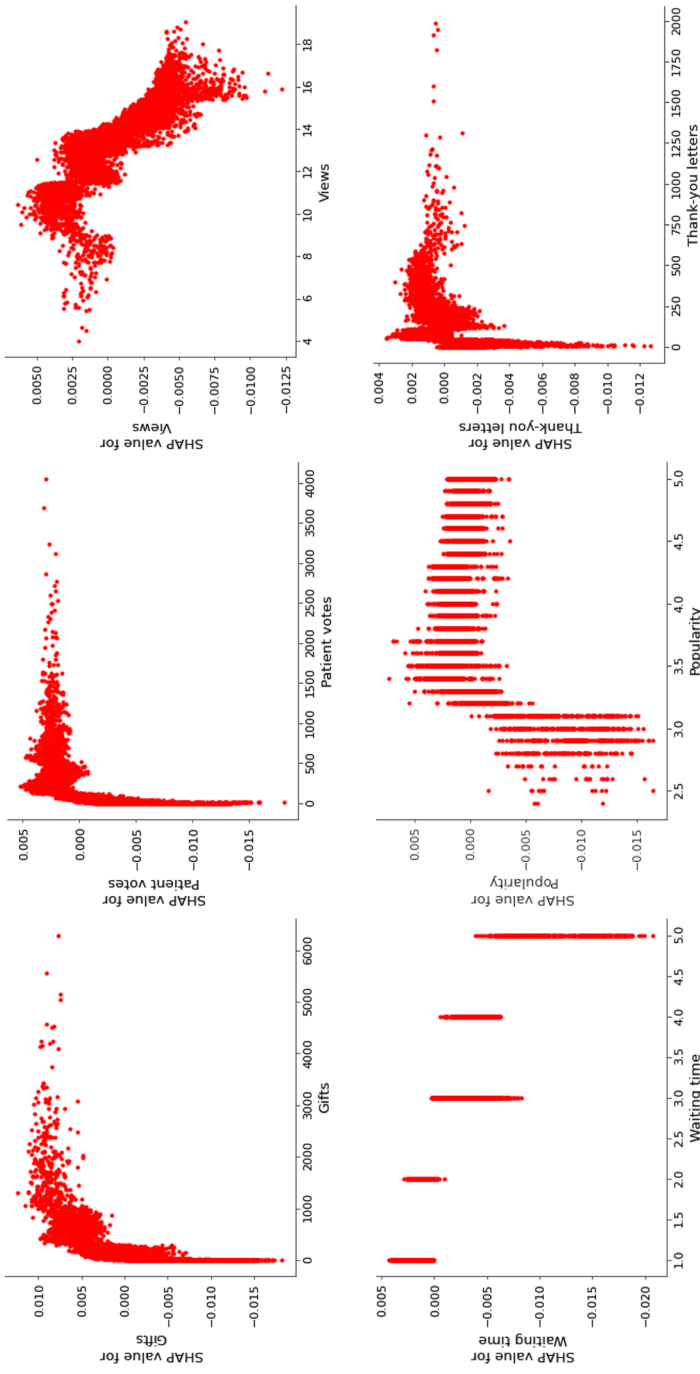


Fig. 5 Dependence plots for interaction characteristics

As shown in Fig. 5, gifts, patient votes popularity, and thank-you letters have a relatively similar distribution in the plot, rapidly increasing initially and maintaining stability gradually. According to this, we understand that gifts, patient votes, popularity, and thank-you letters have a strong positive association with their SHAP value when the number of such variables is low. However, such variables influence service satisfaction positively when their number is low but have only a slight influence when they increase (Li et al. 2019d). Meanwhile, the plot of views presents certain fluctuations of the SHAP value in the intermediate stage, but there is a decreasing trend. According to our analysis, more views do not equal better service satisfaction. Owing to the limitation of COVID-19, patients elected to consult online and view the homepage of physicians broadly, which breaks the balance between online and offline (Cascella et al. 2022). Furthermore, the SHAP value of waiting time declines gradually with the increasing waiting time, and as the waiting time arrives at 5, the descent speed increases. So, the waiting time has a strong negative association with service satisfaction in general, meaning patients are unwilling to spend much time waiting for physicians (Ko et al. 2019).

Third, the impact of the number of free- and fee-based consultations on service satisfaction is the opposite. Specifically, the number of fee-based consultations ($b=0.01980$) enhances service satisfaction, while the number of free consultations ($b=-0.82730$) has the opposite effect, which previous research also identified as a unique phenomenon (Bond et al. 2019; Chen et al. 2022b). Consultation volume ($b=-0.86980$) also negatively influences service satisfaction, which is more substantial than the number of free consultations. Figure 6 illustrates that as consultation volume is less than 4, the SHAP value maintains stability and reaches the maximum value. However, with the rising consultation volume, the SHAP value declines continuously until reaching the minimum value. Thus, we reckon consultation volume has a strong negative effect on service satisfaction due to the limited distribution of health and medical resources (Wan et al. 2021). And the number of free and fee-based consultations affects service satisfaction differently. When the volume is less than 2.5, fee-based consultation volume positively affects service satisfaction, and the number of free consultations has the opposite effect.

However, the two variables negatively impact service satisfaction when the volume is between 2.5 and 4. Finally, when the volume exceeds 4, the fee-based and free consultations positively affect service satisfaction. Based on the overall trend, we can infer that as physicians receive fewer free consultations, patients would be more satisfied with the physician's service. But for fee-based consultations, more fee-based consultations may stimulate physician services, especially when the number of fee-based consultations is small. Due to the influence of economic benefits, the number of fee-based and free services sometimes leads to the opposite effect (Bond et al. 2019; Han et al. 2020). Online healthcare platforms set a suitable price for patients, providing patient services commensurate with the price, improving the patient experience and service satisfaction, and maintaining sustainable development (Zhang et al. 2019). In addition, as patients pay for services provided by online platforms, they may be more serious about online consultations with a better feeling of service (Pauwels and Weiss 2008), thus answering RQ3.

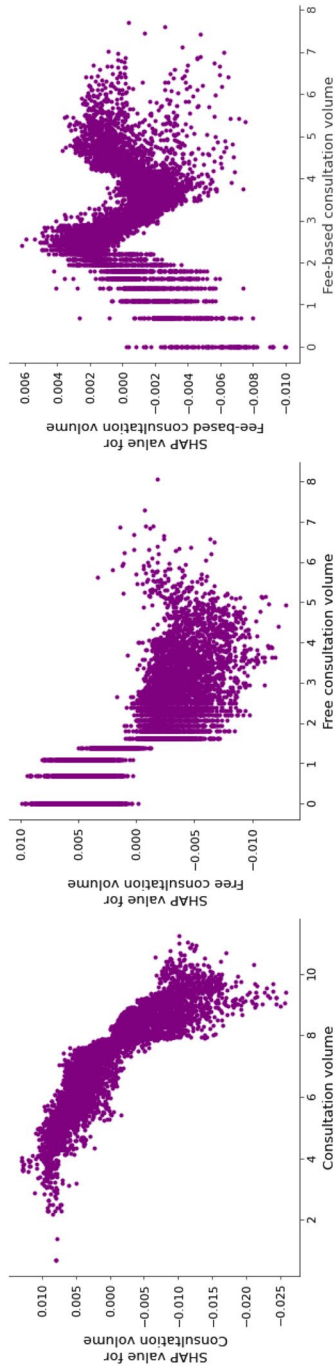


Fig. 6 Dependence plots for consultation volume

5 Conclusion and discussion

This study used machine learning methods on online healthcare platforms to examine the determinants of service satisfaction from three perspectives. First, fewer free and more paid consultations lead to higher service satisfaction, and consultation volume negatively impacts service satisfaction. Second, interaction characteristics positively influence service satisfaction, and patient views and waiting time have negative effects. Third, physician characteristics only have a minor influence on service satisfaction to a certain extent. In summary, these findings have expanded knowledge in the field of online healthcare and provided ideas for further research on online healthcare platforms.

5.1 Theoretical implications

Our study broadens the horizons of service satisfaction of online healthcare platforms by adopting a machine learning approach and makes several contributions to the online healthcare literature. First, our study used total, fee-based, and free consultation volumes to explore their influence on service satisfaction with online platforms. The results indicate that total and free consultation volumes have a relatively strong negative influence on service satisfaction, whereas the fee-based consultation volume has a slightly positive effect. In the context of the COVID-19 pandemic, physicians who cannot generate enough income from consultations will elect to leave their current platform for better platforms (Li et al. 2019a). Prior literature only focused on free or fee consultation services (Li et al. 2019b; Liu et al. 2019; Mezemir 2014) instead of comparing them. By contrast, our research takes advantage of a rich dataset and considers the features of both services. By applying machine learning methods, we obtain information about these services affect service satisfaction, and determine their strength. The integrity of the variables enriches the literature relating to online health platforms and extends the research on service satisfaction.

Second, this study provides insights into comprehensively integrating multiple perspectives to validate how each feature influences service satisfaction with an advanced method. In this study, we used the machine learning methodology to measure features together, yielding high accuracy and interpretability and, thus, superior results. The method also enabled comparisons of all features in a dimension, extending the service satisfaction literature (Sabahi and Parast 2020). The results show that interaction characteristics substantially impact service satisfaction more than physician characteristics. These findings show that our study benefitted from diverse perspectives. Most studies on service satisfaction only demonstrate the influence of one or two features (Liu et al. 2020, 2022a; Wu et al. 2018), whereas this study investigated the predictiveness of interaction characteristics on service satisfaction. In conclusion, our study enriches the online healthcare literature in the context of the during-COVID-19 environment and generates a novel approach to comprehensively exploring the different factors that influence service satisfaction.

Third, using the machine learning approach to compare physician characteristics, interaction characteristics, and consultation volume, we found that physician characteristics only slightly affected service satisfaction. Physician characteristics, including physician title, hospital level, articles, and gender, have a small impact on service satisfaction. In the context of the continuing COVID-19 pandemic, patients prefer to use the identifying information from online healthcare platforms to select a physician. Prior research showed that physicians with high titles have higher popularity with patients (Guo et al. 2017). However, physicians with lower titles offer additional services or accessibility and thus provide superior service quality, so physician titles may not play an important role in service satisfaction (Liu et al. 2014). Few previous studies explored the integrated effects of physician characteristics and service satisfaction. However, our study verified that physician characteristics influence service satisfaction slightly. Male physicians score less service satisfaction than female physicians, but articles, physician titles, and hospital levels negatively affect service satisfaction. This study identifies how physician characteristics affect service satisfaction, thus contributing to the better operation of online healthcare platforms.

5.2 Practical implications

This study also supplies decision-support implications for the operation of platforms in the context of the continuing COVID-19 pandemic. After the COVID-19 outbreak, the role of online health consultations significantly changed. First, according to our findings, increasing volumes of free and fewer volumes of paid consultations significantly and negatively affected service satisfaction. This finding demonstrates that the more patient consultations, the lower the service satisfaction. Due to the excessive number of medical consultations, physicians might provide patients with inadequate solutions to medical problems since they realize they don't make money on free consultations. However, that alone does not confirm that the physician did not provide professional service, and consultation volume can be convincing evidence of their popularity (Wan et al. 2021). On the one hand, physicians should increase online time, enhance service quality, and respond to patients on time (Yang et al. 2015). On the other hand, online healthcare platforms should focus on balancing free and fee-based consultation volumes, thus optimizing platform operations (Wang et al. 2021).

Second, the number of free consultation services is negatively related to service satisfaction; by contrast, physicians with many fee-based consultations usually have high service satisfaction. According to the influence of economic benefits and medical resources, fee-based and free consultations may generate different effects (Han et al. 2020; Wan et al. 2021). Patients may be more serious about consultations and receive high-quality service if they pay for consultations (Pauwels and Weiss 2008). Meanwhile, fee-based consultations can screen out patients who need to consult urgently and maintain sustainable development in the future. Therefore, online healthcare platforms should set reasonable prices and provide matching

services, which increase revenue based on improving the service satisfaction of patients.

Third, our results show that interaction characteristics, including thank-you letters, patient votes, and gifts, improve service satisfaction. Such factors strongly and positively moderate online physicians' ratings and income (Wang et al. 2020; Zhou et al. 2022). With increasing patient support, service satisfaction improves, attracting more patients. Service satisfaction depends on those factors derived from patients' feedback. Thus, interaction characteristics play a significant guiding role, as other patients refer to the indicators when selecting the proper physician, which pushes physicians to provide better service.

5.3 Limitations and future directions

Our study has several limitations and future directions. First, we focused on one of the best online healthcare platforms in China, limiting our mined dataset to basic physician information. Several perspectives, such as interpersonal skills, disease severity, patient characteristics, and social sharing, may drive service satisfaction, and some control or moderating variables may also influence service satisfaction.¹ Therefore, obtaining more relevant data and constructing more interesting variables from similar platforms is necessary. In addition, since we collected our sample from China, this may limit the generalizability of our findings to other developing or developed countries. As a result, we encourage future research to validate our findings using samples from other regions. Second, we only used the number of fee-based consultations instead of their price. However, given that the price of consultations is related to informational issues, we view this shortcoming as a limitation for future research to address. Future research might consider collecting consultation prices and investigating the reasons behind them. Third, some unobserved individual features of physicians may affect service satisfaction. For example, some studies included physicians' subjective features to measure their effects on the dependent variable (Liu et al. 2020, 2022a). Future research could extend the data acquisition process to obtain a more diverse set of variables and collect broader data over a longer period to enrich our findings. Finally, machine learning as an advanced method can improve the accuracy and convenience of research. Future studies should advocate for a multi-methodology framework with machine learning as a viable and desirable way forward.

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

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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