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What drives patients to choose a physician online? A study based on tree models and SHAP values

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***Abstract*— Smart healthcare is changing our lives. As an emerging medical pattern, online medical platform is arising from the combination of traditional medical resources and Internet platform, which largely resolve the disequilibrium of offline medical resources in China. Compared with offline healthcare, online platforms shorten the distance between patients and medical resources and give patients more options to seek medical treatment during the COVID-19 epidemic. In order to better help and guide patients in making decisions, the platform provides physicians' treatment information for patients' reference. This information describes the physician's diagnostic capability and service level from different dimensions, such as the physician's specialty, the number of gifts received from patients, etc., which are important basis for patients to choose a physician. For the platform and physicians, it is crucial to understand patients' preferences for different characteristics of physicians in the consultation process, in order to manage data more targeted. This paper use machine learning methods to build a prediction model of physician's characteristics data on incremental volume of consultation to study patients' preferences in medical consultation. Most existing studies use linear models, but given the complexity of patient preferences, they may have greater limitations in reflecting patients' choice logic. Therefore, this paper turn to more complex models on the training data. For the lack of interpretation of complex models, this paper uses a Shapley Value-based approach to parse the model's feature contributions to obtain patients' preferences for physician information. From the perspectives of local interpretation, global interpretation and interaction effect, this paper obtains regular conclusions on patients' preferences for physicians' information, and discusses the management insights in the context of online platform management and physicians' word-of-mouth maintenance.**

***Index Terms*— Online Medical Platform, Machine Learning, Tree Models, SHAP Values**

I. INTRODUCTION

Inheriting the excellent characteristics of Internet technology such as efficiency and convenience, smart healthcare is providing more and more help in our life. Especially in COVID-19 epidemics, when people are affected by quarantine policies that prevent them from accessing medical care offline as conveniently as before, online medical services can provide a viable solution for people who seek medical help. In this scenario, patients can choose their preferred physician and consult with them through the online platform at any time and any place [1], [2].

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In fact, there is an information asymmetry inherent in healthcare services, which stems from the fact that the physician can know the condition of the patient from observation and testing, but the patient cannot immediately assess the quality of the service provided by the physician [3]. More importantly, the Internet environment is prone to a perception of uncertainty in the service process, and patients are often not fully certain about their choice of medical services [4]. To reduce this information asymmetry and uncertainty, patients often seek out Physician-related information to help them make decisions [5].

Therefore, online medical platforms provide information of various physicians for patients to refer to [6], [7], which includes not only the physician's personal features (e.g., title, gender, etc.), but also information about the physician's historical behavior in participating in online consultations on the platform (e.g., online votes, thank-you letters, etc.). This feedback is very important in the physician-patient relationship [8]. Just as information about a product on an e-commerce platform can promote a buyer's purchase, so can diverse physician feature data influence a patient's choice of physician [9], [10]. In this article, we want to develop a plausible model to explore patients' preferences for physician features in online consultation behavior.

The role of physician information has been studied by some reseachers. Liu et al. [11] found that the efforts of physicians can increase their reputation and visibility. Fung et al. [12] trial showed a general preference for highly technically qualified physicians and a significant proportion of the patient sample preferred highly interpersonal qualified physicians. In recent years, platforms with physician scoring have become a way for patients to provide feedback and access information on physician performance, and can improve the efficiency of the healthcare industry [13], [14]. Gao et al. [15] found a significant correlation between ratings and the number of consultations, further validating the role of website information in patient selection of physicians.

Furthermore, researchers want to explore what kind of information would have the positive effect on patient choice. In addition to researches which using traditional social experiments or questionnaires, some researches built Linear Regression (LR) model to analyze the influence by using increment volume of online consultations in a certain period as the substitute for patients' preferences. In other words, the higher the number of online consultations a physician has compared to other physicians, the more likely patients are to choose him in the process of selection on the online medical platform. Deng et al. [16] found that both physicians' reputation and contribution have positive effect on the increase in online patients, but the influence of a physician's reputation varies. Gong et al. [17] explored that physicians' quality and online reputation can significant affect patients' selection, and physician's gender can enhance the influence. Hu et al. [18] used the length and volume of the review on physicians' consultations to figure out their roles in the physician-patient relationship. Those researches used incremental volume of online consultations as dependent variable, and use other feature which can be collected through the physician's personal homepage as the independent variables. However, the performance of linear model for feature-based data is weak and cannot capture the nonlinear relationship between the dependent variable and the independent variable, which causes the model to have weak predictive power and problems such as underfitting. This can be a very big challenge for making models more accurate about the way patient select the physician through the feature information.

As a result, this paper tries to use machine learning models with stronger feature representation, including Lasso[19], Multilayer Perceptron (MLP)[20], and tree models such as Decision Tree, Random Forest [21], Gradient Boosting Decision Trees (GBDT) [22], eXtreme Gradient Boosting (XGBoost) [23] and Light Gradient Boosting Machine (LightGBM) [24] have been applied in various field like pharmacokinetic property prediction [25] and credit scoring [26]. In contrast to their excellent predictive performance, these nonlinear models just like a "black boxes"—— lacking intuitive explanations of the input variables compared to linear models, which is crucial in the judgment on the importance of input variables. To solve the above problems, we turn to Shapley Additive exPlanations (SHAP) [27], [28], a concept originate from economic game theory for utility allocation called Shapley Value [29] and can add interpretability to models, which can illustrate the the contribution of each input variables on the outcome of the "black box" model.

In this study, we introduce a machine learning model that can better represent the patient selection process for physicians, and interpret the model by the SHAP method to analyze patients' preferences for information provided by the platform. In terms of result analysis, we analyze the feature results through local interpretation, global interpretation and interaction effect to more intuitively reflect the pattern of patients' choice of physicians, and make meaningful suggestions for online platform governance and physician word-of-mouth maintenance.

II. METHODOLOGY

To better explain the role of physician features in patient online selection through rational models, we divided the process into three broad areas which shown in Fig.1: Data Processing, Model Evaluation, Model Explanation.

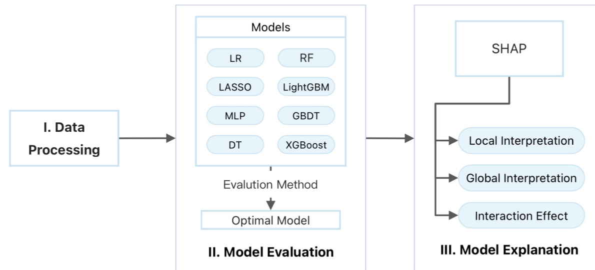

Fig. 1. The procedure of physician features analysis

A. Data Processing

1) Data collection: The data of physician features is collected on *Good Doctor Online*[1], one of the biggest online medical platform with more than 200,000 registered physicians. By applying to their open dataset (www.haodf.com/opendata/home), we obtain the physician data from 2018 to 2020, containing kinds of features on the physician homepage Fig.2. Using 2018 physician data as a base, we consolidate and counte a total of 185,605 physicians with complete, error-free information.

Fig. 2. An example of a physician's homepage (Oct 11, 2021)

2) Variables Selection: We focus on features that the patient may notice during the online visit. Combining previous related research [16], [17], [18] and the information presented on the physician's homepage which can be easily accessed by the patients, we finally choose the following features as independent variables: "Recommendation Index", "Number of Articles", "Number of Homepage Views", "Number of Appointments (for offline consultation)", "Number of Patient Votes", "Number of Thank-you Letters", "Number of Gifts", "Gender". We use aggregate data on these features to represent different aspects of physicians' abilities. Among them, The "Recommendation Index" is

[1]The platform website is https://www.haodf.com/

calculated by the platform as a comprehensive recommendation rate. And we treat "Gender" as a dummy variable, devided into "Gender: Male", "Gender: Female", "Gender: Unknown". It is worth mentioning we omitted the "Number of" in the following for simplicity.

As for the dependent variable, we use the incremental volume of consultations received by physicians on the platform during 2018-2020, which can reflect the patient's choice as interacting with a specific physician. In addition, we use logarithmic processing to ensure the normality of the data set distribution.

B. Model Evaluation

Now, supervised machine learning has produced many new algorithms, and deep learning as one of the representative can achieve high prediction accuracy with a considerable number of parameters. In the scenario of this article, there are a few features in the physician data, and the model needs reasonable explanation, so we choose logistic regression, Lasso, Multilayer Perceptron (MLP), Decision Tree and its related models including Random Forest, GBDT, XGBoost, LightGBM.

Lasso means "Least absolute shrinkage and selection operator", is a regression analysis with ℓ^1 regularization which can remove unimportant variables from the model. MLP is a feed-forward artificial neural network model that maps multiple datasets of input to a single dataset of output. Decision Tree (DT) is a tree-like model which can decompose a complex decision process into a simple set of decisions. Random Forest (RF) are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest [21]. Boosting tree utilizes an additive model and a step-forward algorithm to optimize the learning process and GBDT uses the value of the negative gradient of the loss function in the current model as an approximation of the residual of the boosting tree algorithm in the regression problem to fit the next regression tree g_m [22].

$$f_m(X) = f_{m-1}(X) + \rho_m g_m(X) \tag{1}$$

$$\rho_m = \arg\min_{\rho} \sum_{i=1}^{n} L(y_i, f_{m-1}(X_i) + \rho_m g_m(X_i)) \tag{2}$$

The idea of XGBoost is similar to GBDT, but the second derivative of the loss function is used for optimization, and a normalized term $\Omega(f_k)$ is added to the object to avoid overfitting[23].

$$Obj = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{3}$$

In order to improve the efficiency of model, LightGBM applied Gradient-based One-side Sampling (GOSS) and reduce the number of data instances and the number of features Exclusive Feature Bundling (EFB) to the process of training, which can reduce the number of samples and features[24].

In order to evaluate the performance of the models, we turn to three statistical indicators including Mean of Squared Error (MSE), Coefficient of Determination (R^2) and Mean Absolute Error (MAE).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{5}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{6}$$

On the basis of the ten features extracted from the processed dataset, the performances of the models are then compared by a ten-fold cross-validation on the training set. The results are shown in Table I.

TABLE I
MODEL COMPARISON RESULTS ON PROCESSED DATASET

Model	MSE	R^2	MAE
LR	2.6266	0.3258	1.2182
LASSO	2.8078	0.2794	1.2770
MLP	2.7143	0.3034	1.2807
RF	1.6096	0.5867	0.9414
DT	1.6473	0.5770	0.9496
GBDT	1.5307	0.6069	0.9085
XGBoost	**1.5302**	**0.6071**	**0.9071**
LightGBM	1.5306	0.6070	0.9083

According to the results summarized in the table, XGBoost performs better than others, so we take XGBoost for the following analysis.

C. SHAP

Shapley Additive exPlanations (SHAP) is proposed to interpret the output of model by reasonably allocating the value to each input features [27]. Assuming a machine learning model f with input $\boldsymbol{x} = (x_1, x_2 ... x_n)$ and with n different features for a certain input $\boldsymbol{x} = \boldsymbol{x_c}$, SHAP carries this framework over to the interpretation of variables in the model:

$$f(\boldsymbol{x}) = g(\boldsymbol{x'}) = \phi_0 + \sum_{i=1}^{M} \phi_i x'_i \tag{7}$$

where $\boldsymbol{x'}$ is the feature vector formed by the binary mapping of the features in $\boldsymbol{x}$, x'_i can be interpreted as the existence of the certain feature i with observed ($x'_i = 1$) or unknown ($x'_i = 0$), ϕ_i is the real contribution of the feature to the output value $f(\boldsymbol{x})$, and M is the number of input features. It is worth mentioning that ϕ_0 represents that the features of this data are all unknown, that is, the mean value of the model output.

Similar to the distribution pattern of the cooperation benefits in Shapley Value [29], SHAP defines the contribution of a certain feature i to the output value of the input $\boldsymbol{x}$ as

$\phi_i(\boldsymbol{x})$, and the calculation formula is:

$$\phi_i(\boldsymbol{x}) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(M - |S| - 1)!}{M!} \left[f(\boldsymbol{x}, S \cup \{i\}) - f(\boldsymbol{x}, S) \right] \tag{8}$$

where N is the set of all feature in $\boldsymbol{x}$, $f(\boldsymbol{x}, S)$ refers to the output when input $\boldsymbol{x}$ with the set of features S observed in the model.

Due to the challenge of estimating the output with partial loss of features of input data, Lundberg et al. [27], [28] introduce Tree SHAP algorithm to solve it by using the special structure of the tree model, which can calculate the contribution of each features in every input data precisely and efficiently. This algorithm is very suitable for studying the value of physician's features .

III. Results and Analysis

A. Patient Information Preference

In this subsection, we hope to analyze the patient information preference during the online consultation process from a local interpretation of the physician's features. After obtaining the model that best reflects the pattern of patient online consultation behavior, we interpreted the model using the SHAP method to obtain the contribution of each physician feature to the incremental volume of consultations, which symbolizes the patient's preference for the feature. In order to distinguish the different value of the physician feature, we called the magnitude "feature value", and the contribution to the output "SHAP value". Fig.3 shows the features contribution map of a single physician data, indicating the output from the base value (output of the model without adding features) adding up the values contributed by all the features and finally obtaining the model output. Some of this contribution is positive (red) and some is negative (blue). If a feature generates a positive SHAP value, it means that the patient favors the feature during the consultation and has a tendency to choose the physician based on it. And the larger the SHAP value, the greater the feature's contribution to the physician's attractiveness. On the contrary, if the feature generates a negative SHAP value, it means that the presence of the feature causes the patient to doubt the physician's ability to consult the physician and affects the physician's attractiveness to the patient.

We integrated the values of all physicians features, and get the distribution trend of feature value and SHAP value, consisting of different feature points for each physician data, as shown in Fig.4. Each dot symbolizes a feature of a specific physician, and the color represents the magnitude of feature value (red-high, blue-low) and the horizontal coordinate represents SHAP value. From the figure we can see that the distributions of "Recommendation Index", "Appointments", "Thank-you Letters", "Gifts" and "Articles" are similar: when the feature value is large, its SHAP value is larger. On the contrary, when the feature value is small, its SHAP value is lower. In other words, in the online consultation scenario, when patients see a small value of these features, they have doubts about the physician's consultation ability and service quality. However, when the value of these features is large, patients feel trust in the physician's ability and have a preference for medical treatment. Our results show that in the patient's perspective, the magnitude of these features information positively related to the comprehensive level of the physician's online consultation. This indicates that these features have inducing effect on patients' choice of physicians, which can be regarded as physicians' word-of-mouth.

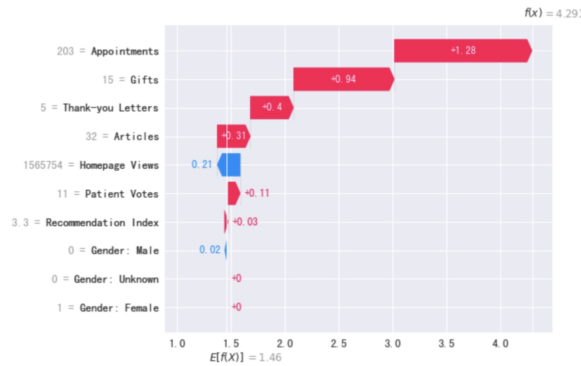

Fig. 3. A example of features contributions to output value

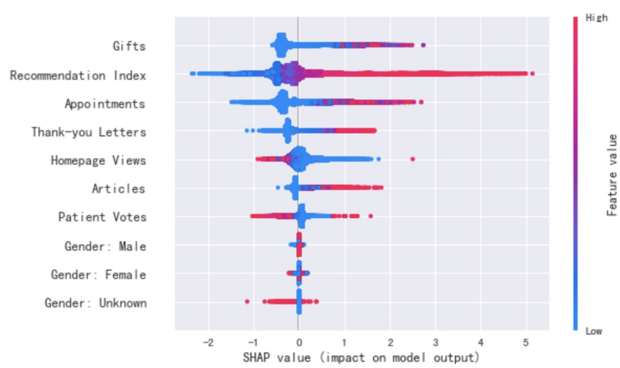

Fig. 4. Values distribution from all physician features

B. Importance of physician features

In this subsection, we hope to analyze importance of physician features through a global variable.

Similar to the analysis of indicator significance in the linear model [16], [18], to better analyze the role of physician feature from a global perspective and to add a quantitative analysis approach, we treat the SHAP values of each physician feature globally: the absolute value of the SHAP value is taken as the mean value, i.e., we do not distinguish between positive and negative patient preferences and only focus on the impact of features on patients' choice of online medical care. Finally, each category of characteristics corresponds to a global index, which is called the "global feature influence index" of physician features in this study. The index is ranked according to the order of numerical magnitude, and the following Fig.5 is obtained. Unlike other features, the influence indexes of gender: “Gender: Male“, “Gender: Female“ and “Gender: Unknown“, is very small. In other words, gender information has very little impact on patient decision making compared to other physician features. This may be because the online environment eliminates the need for face-to-face communication and patients are less apprehensive about being in front of a different gender physician.

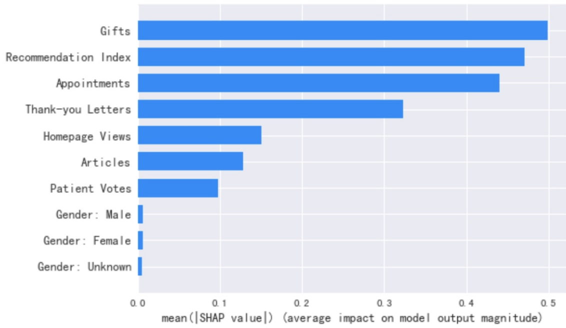

Fig. 5. Global influence index of physician’s features

In the XGBoost model, using the $frequency$, $coverage$, $informationgain$ and other indicators that related to the model structure can be integrated to get the generalized importance of feature based on model performance, named “feature_importance“. To test the effect of SHAP value on model performance, we determine the unimportance of physician features according to the reverse sequence of the global feature influence index, the feature_importance (FI) and random (RAN). Features are removed one by one from XGBoost model through different sequences above, and the ten-fold cross validation MSE, R^2 and MAE results were recalculated accordingly. Fig.6 shows the performance of the model on the remaining features after removing features in different turns on datasets.

Removing features according to the reverse sequence of the global feature influence (SHAP) attains better performance in the model than the other three sequences. This demonstrates that the ranking, obtained by calculating the absolute mean of the feature SHAP values, is excellent for diagnosing the importance of features in model prediction, and is even better than the feature_importance obtained from the information gain of the dataset (at the 7th remove), based on the decline of loss function which directly related to model prediction accuracy.

C. Interaction Effect

Just like the use of interaction terms in econometrics which measure the impact of one variable depends on the value of another [30], we wish to analogize a conceptual pattern to explain the interaction between physician features for patient selection. In this part, we use “substitution effect“ and “complementary effect“, like the commodity relationship in economics, to explain the relationship between two features. The former means that the SHAP value of one feature to

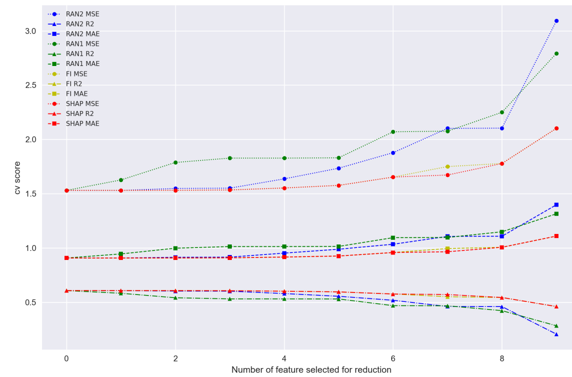

Fig. 6. Feature reduction comparison on dataset

the model output decrease as the value of another feature increases, the latter represents the opposite trend.

After verifying the importance of the “Recommendation Index“ provided by online medical platforms for patient’s choice of physician, we want to explore the interaction of this index with other physician features in the process. Fig.7 shows the interaction between “Recommendation Index“ and other features (“Appointments‘, “Thank-you Letters“, “Gifts“ and “Articles“), which we mentioned before as the feature that have inducing effect on patient online consultation. The horizontal axis of the graph represents the feature value of the “Recommendation Index“, while the vertical axis represents its SHAP value, and the color of the dots represents the magnitude of other features at this case. We can see that plots in Fig.7 have similar characteristics: for the same feature value of “Recommendation Index“, its SHAP value of the index decreases as the magnitude of other features increase, which conceptually consistent with “substitution effect“.

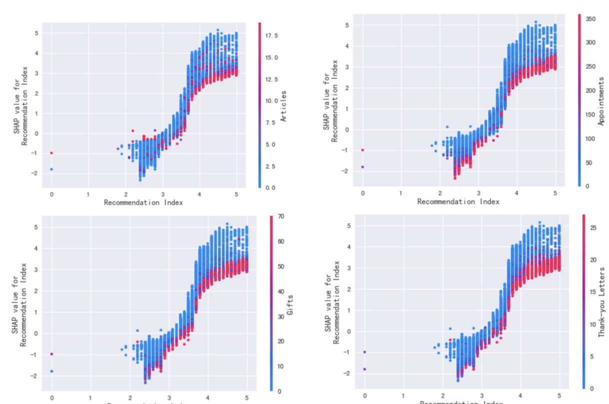

Fig. 7. Substitution effect between Recommendation Index and other features

A plausible explanation is that the SHAP values of the features in our model reflect their influence on patients’ choice of physician in the online medical platform. From the patient’s perspective, the “Recommendation Index“ provided by the platform is more comprehensive in its assessment of the physician’s online consultation ability and covers part of the information of other features. So the degree of its influence on the patient’s selection will be divided away by other features, demonstrated by the “substitution effect“ in the model, which is more significant when the values of other features are larger.

As for the interaction between features other than the “Recommendation Index“, we have drawn a similar plot (Fig. 8) using the “Thank-you Letters“ and “Applications“ as an example. When the value of the “Thank-you Letters“ feature is relative small (0-200), the larger “Applications“ feature has a significant boost to the SHAP value of the former, which is consistent with “complementary effect“. This could indicate that there is an informational promotion between “Thank-you Letters“ and “Applications“, such that their roles are mutually reinforcing in terms of their impact on patients’ selection of physician.

Fig. 8. Complementary effect between Thank-you Letters and Appointments

IV. MANAGEMENT INSIGHTS

This study hopes to draw on findings related to patients’ online consultation behavior to provide management insights into the governance of online platforms and the maintenance of physicians’ word-of-mouth.

First, the platform can intuitively understand the types of physician preferred by patient during online consultant. The platform can display these word-of-mouth in a more prominent position on the physician’s homepage and distinguish them from other physicians’ characteristics. This will not only improve the efficiency of patients’ choice of physicians and their experience during online consultation, but also boost the platform’s customer acquisition.

Besides, in the face of the huge volume of physicians, online platforms use recommendation technology to help patients narrow down their choices based on their preferences and reduce the cost of online searching. The current mainstream recommendation algorithm mainly matches the patient’s consultation text content by mining the physician’s characteristic information, realizing the overlap between the patient and the physician in terms of disease characteristics, and finally selecting the physician group with higher similarity for sorting [31], [32]. By understanding patients’ preferences, we can integrate these factors into the idea of recommendation algorithm, as shown in Fig. 9, where the red process represents the selection process based on patients’ online consultation behavior discussed in this paper, which can be combined with the black text-based representation of the recommendation process to rank physicians. Doing so not only takes into account the range of diseases that the physician specializes in, but also takes into account the patient’s preference habits in choosing a physician, i.e., recommends a physician for the patient that meets his or her multifaceted needs, which plays a role in promoting more accurate recommendations for the platform.

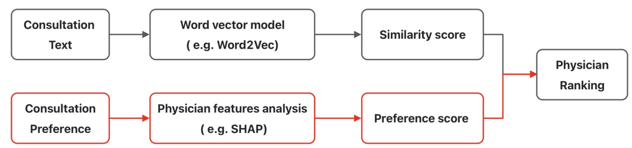

Fig. 9. Online physician recommendation algorithm combined with patient consultation behavior analysis

Furthermore, from the substitution effect between features, patients recognize the rationality of “Recommendation index“ in the integration of physician feature information for the demonstration of physician consultation ability, further indicating the importance of this index on online resource allocation. In addition to increasing the variety of information included in the platform’s calculation of “Recommendation index“, which makes the index more accurate in assessing physicians’ consultation ability and service level, the platform can also balance the index among different types of physicians to maximize its own revenue. On the one hand, the platform can appropriately increase the “Recommendation index“ of some active physicians who have just entered the platform to make up for the lack of their word-of-mouth volume; on the other hand, it can reduce this index of some physicians who entered the platform early to accumulate a lot of word-of-mouth but have been inactive in recent years. This can make the platform’s physician group exposed to patients always maintain an active consultation status.

For physicians, on the one hand, patient’s preference for certain kind of information allows physicians to purposefully spend more effort on specific information enhancement to build a better and closer physician-patient relationship. On the other hand, the complementary relationship between some features provides targeted suggestions for physicians, and physicians who are new to the platform can use this relationship to gain patients’ favor more quickly.

V. CONCLUSIONS

In this article, we attempt to analyze the impact of physician features provided by the online medical platform on patient's choice of physician. To make our results generalizable, we used the entire physicians data provided by Good Doctor Online, selected the feature information on the physicians' homepage as the independent variable, and used the logarithmic incremental number of consultations over two years as the dependent variable. We use a combination of XGBoost and SHAP to train and explain our model, which can maintain the performance of the model and have the interpretability of the variables. On this basis, we obtained the contribution of each feature of all physicians to consultation output, which is the SHAP value of the feature, to reflect the information preference of patients in terms of physician selection.

In terms of results, the study first analyzed patients' preferences for physician information provided online platform and found that patients tended to believe in "Gifts", "Recommendation Index", "Appointments", "Thank-you Letters" and "Articles" during online consultation compared to other features, which they think can be used to assess physicians' consultation ability and service quality. Second, we obtain a "global feature influence index" to explain the impact of the features on patients globally, and it was found that the impact of gender-related features is small, indicating that patients did not attach much importance to the physician's gender during online consultation. Besides, we compared this index with "feature_importance", which is generated by XGBoost model structure, and found that this SHAP-based index is also useful for explaining the prediction accuracy of the model. Third, the study focused on the interaction effect between different physician word-of-mouth during the online consultation process. We found that there is a "substitution effect" between the "Recommendation Index" and the rest of the features set, meaning that this index contains some of the information provided by other word-of-mouth and patients agree on its role in providing a comprehensive overview of physician competencies. On the other hand, there is a "complementary effect" between "Thank-you Letters" and "Appointments", i.e., patients' preference for one type of word-of-mouth feature increases with the other word-of-mouth feature increase, showing the complementary information for physician competency assessment. Finally, this study provides managerial insights into the governance of online platforms and the maintenance of physician word-of-mouth. The platform can be improved and developed by improving the efficiency of data governance, improving the recommendation algorithm, and enhancing the relevance of operational strategies, and physicians can maintain their own word-of-mouth in a purposeful manner to maintain their attractiveness to patients.

Limited by the experimental conditions, our study does not include textual information of physician features in the homepage, like review information, physician profiles, which need to be further processed before putting into the model. On the other hand, the physician dataset needs to be constantly updated to meet the ever-changing needs of the platform.

Future research could try to incorporate and process textual information of physicians on online medical platforms to meet a more comprehensive assessment of features. In addition, a deeper study of physician feature preferences for different kinds of patients can be attempted using patients' online consultation data, combining with physician features.

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REFERENCES

[1] J. G. Anderson, M. R. Rainey, and G. Eysenbach, "The impact of cyberhealthcare on the physician–patient relationship," *Journal of medical systems*, vol. 27, no. 1, pp. 67–84, 2003.

[2] L. Yan and Y. Tan, "The consensus effect in online health-care communities," *Journal of Management Information Systems*, vol. 34, no. 1, pp. 11–39, 2017.

[3] X. Liu, X. Guo, H. Wu, and T. Wu, "The impact of individual and organizational reputation on physicians' appointments online," *International Journal of Electronic Commerce*, vol. 20, no. 4, pp. 551–577, 2016.

[4] E. Sillence, P. Briggs, P. Harris, and L. Fishwick, "A framework for understanding trust factors in web-based health advice," *International Journal of Human-Computer Studies*, vol. 64, no. 8, pp. 697–713, 2006.

[5] S. Karimi and F. Wang, "Online review helpfulness: Impact of reviewer profile image," *Decision Support Systems*, vol. 96, pp. 39–48, 2017.

[6] T. Lagu, N. S. Hannon, M. B. Rothberg, and P. K. Lindenauer, "Patients' evaluations of health care providers in the era of social networking: an analysis of physician-rating websites," *Journal of general internal medicine*, vol. 25, no. 9, pp. 942–946, 2010.

[7] S. Grabner-Kräuter, M. K. Waiguny *et al.*, "Insights into the impact of online physician reviews on patients' decision making: randomized experiment," *Journal of medical Internet research*, vol. 17, no. 4, p. e3991, 2015.

[8] G. Ren and T. Hong, "Examining the relationship between specific negative emotions and the perceived helpfulness of online reviews," *Information Processing & Management*, vol. 56, no. 4, pp. 1425–1438, 2019.

[9] B. Abrahao, P. Parigi, A. Gupta, and K. S. Cook, "Reputation offsets trust judgments based on social biases among airbnb users," *Proceedings of the National Academy of Sciences*, vol. 114, no. 37, pp. 9848–9853, 2017.

[10] S. K. Ariffin, T. Mohan, and Y.-N. Goh, "Influence of consumers' perceived risk on consumers' online purchase intention," *Journal of Research in Interactive Marketing*, 2018.

[11] X. Liu, X. Guo, H. Wu, and D. Vogel, "Doctor's effort influence on online reputation and popularity," in *International Conference on Smart Health*. Springer, 2014, pp. 111–126.

[12] C. H. Fung, M. N. Elliott, R. D. Hays, K. L. Kahn, D. E. Kanouse, E. A. McGlynn, M. D. Spranca, and P. G. Shekelle, "Patients' preferences for technical versus interpersonal quality when selecting a primary care physician," *Health services research*, vol. 40, no. 4, pp. 957–977, 2005.

[13] J. Sarasohn-Kahn, "The wisdom of patients: Health care meets online social media," 2008.

[14] M. N. Kamel Boulos and S. Wheeler, "The emerging web 2.0 social software: an enabling suite of sociable technologies in health and health care education 1," *Health Information & Libraries Journal*, vol. 24, no. 1, pp. 2–23, 2007.

[15] G. G. Gao, J. S. McCullough, R. Agarwal, and A. K. Jha, "A changing landscape of physician quality reporting: analysis of patients' online ratings of their physicians over a 5-year period," *Journal of medical Internet research*, vol. 14, no. 1, p. e2003, 2012.

[16] Z. Deng, Z. Hong, W. Zhang, R. Evans, and Y. Chen, "The effect of online effort and reputation of physicians on patients' choice: 3-wave data analysis of china's good doctor website," *Journal of medical Internet research*, vol. 21, no. 3, p. e10170, 2019.

[17] Y. Gong, H. Wang, Q. Xia, L. Zheng, and Y. Shi, "Factors that determine a patient's willingness to physician selection in online healthcare communities: A trust theory perspective," *Technology in Society*, vol. 64, p. 101510, 2021.

[18] Y. Hu, H. Zhou, Y. Chen, J. Yao, and J. Su, "The influence of patient-generated reviews and doctor-patient relationship on online consultations in china," *Electronic Commerce Research*, pp. 1–27, 2021.

[19] R. Tibshirani, "Regression shrinkage and selection via the lasso," *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 58, no. 1, pp. 267–288, 1996.

[20] M. W. Gardner and S. Dorling, "Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences," *Atmospheric environment*, vol. 32, no. 14-15, pp. 2627–2636, 1998.

[21] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.

[22] J. H. Friedman, "Greedy function approximation: a gradient boosting machine," *Annals of statistics*, pp. 1189–1232, 2001.

[23] T. Chen, T. He, M. Benesty, V. Khotilovich, Y. Tang, H. Cho, K. Chen *et al.*, "Xgboost: extreme gradient boosting," *R package version 0.4-2*, vol. 1, no. 4, pp. 1–4, 2015.

[24] G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu, "Lightgbm: A highly efficient gradient boosting decision tree," *Advances in neural information processing systems*, vol. 30, 2017.

[25] X. Yang, Y. Wang, R. Byrne, G. Schneider, and S. Yang, "Concepts of artificial intelligence for computer-assisted drug discovery," *Chemical reviews*, vol. 119, no. 18, pp. 10 520–10 594, 2019.

[26] Y. Xia, C. Liu, Y. Li, and N. Liu, "A boosted decision tree approach using bayesian hyper-parameter optimization for credit scoring," *Expert Systems with Applications*, vol. 78, pp. 225–241, 2017.

[27] S. M. Lundberg, G. G. Erion, and S.-I. Lee, "Consistent individualized feature attribution for tree ensembles," *arXiv preprint arXiv:1802.03888*, 2018.

[28] S. M. Lundberg, G. Erion, H. Chen, A. DeGrave, J. M. Prutkin, B. Nair, R. Katz, J. Himmelfarb, N. Bansal, and S.-I. Lee, "From local explanations to global understanding with explainable ai for trees," *Nature machine intelligence*, vol. 2, no. 1, pp. 56–67, 2020.

[29] L. Shapley, "Quota solutions op n-person games1," *Edited by Emil Artin and Marston Morse*, p. 343, 1953.

[30] J. Jaccard, R. Turrisi, and J. Jaccard, *Interaction effects in multiple regression*. Sage, 2003, no. 72.

[31] H. Jiang and W. Xu, "How to find your appropriate doctor: An integrated recommendation framework in big data context," in *2014 IEEE Symposium on Computational Intelligence in Healthcare and e-health (CICARE)*. IEEE, 2014, pp. 154–158.

[32] B. Tian, Y. Zhang, X. Chen, C. Xing, and C. Li, "Drgan: a gan-based framework for doctor recommendation in chinese on-line qa communities," in *International Conference on Database Systems for Advanced Applications*. Springer, 2019, pp. 444–447.