Personalized recommendation framework design for online tourism: know you better than yourself

Xiaoqian Wang
School of Tourism and Hotel Management, Hubei University of Economics, Wuhan, China

Received 29 May 2020
Revised 15 September 2020
Accepted 21 September 2020

Abstract

Purpose – This study aims to create an idea and a framework to enhance customer stickiness and improve transformation efficiency flow of tourism products from online to offline platforms through the application of personalized recommendation technology.

Design/methodology/approach – Studies on an overview of progress in current personalized recommendation research, business scenario analysis of online tourism and some possible logical limitations discussion are required for improvement. This study clarifies concepts including online tourism user behavior and generated data, user preference themes and spaces, user models and image and user-product (two-dimensional matrix, etc.). The author then creates a user portrait based on behavior data convergence to locate the user's role from both horizontal and vertical dimensions and also clear the logical levels and associations among them, verifying the similarity in measurement and calculation and optimizing the implementation of the personalized recommendation program under online tourism business scenarios.

Findings – By providing a framework design about personalized recommendations of online tourism including a flow from data collection to a personalized recommendation algorithm selection, logical analysis is established while the corresponding personalization algorithm is improved.

Originality/value – This study show a logical shift of personalized recommendations in online tourism management from focusing on the simple collection of travel information and the logical speculation of tourism products to focusing on the individual behavior of potential travelers.

Keywords Personalized recommendation framework, Online tourism, Individual behavior, Preference analysis, Persona, Algorithm selection

Paper type Research paper

1. Introduction

The Internet era brought in rapid improvement of information technology, and with it hastened a shift in a lot of traditional industries, including tourism—an information-sensitive industry (Jasmina *et al.*, 1980). The tourism industry quickly adopted technologies such as travel portals, online ticket purchasing, hotel bookings, etc. (Oliveira and Martins, 2010). As we enter the age of big data, these changes become more impressive and inspiring.

With the evolution of big data, availability of information has grown exponentially. Mass information can not only be widely disseminated through the Internet but also be more effectively applied through big data technology, including the storage, collection and mining of data generated from mass information (Jiawei and Micheline, 2006). For tourism, there are now more opportunities to utilize this data to assist customers to have better travel experiences, e.g. with a personalized recommendation system, which is well known as an important foothold of "big data application" (Pazzani, 1999). In order for retailers to know what users want, providing recommendation services to online merchants is an important strategy (Shih *et al.*, 2002).

Nowadays, the algorithm model of personalized recommendation has been proven more sufficient as the technical threshold of mainstream model implementation is not very high (Guoxia, 2012). The personalized recommendation system has been implemented in more and

Industrial Management & Data Systems

0263-5577
DOI 10.1108/IMDS-05-2020-0278

more business domains, e.g. TV advertising (Ardissono *et al.*, 2003), online shopping (Kim *et al.*, 2009), social software (Liu *et al.*, 2011) and even Tourism (Huang and Bian, 2009). The common value of personalized recommendation in these domains is to guide and help users to reasonably match their personalized needs in diverse products and services (Resnick and Varian, 1997), and to maximize their satisfaction and get more enjoyment (YinC *et al.*, 2018). But it is also worth paying attention to that the occurrence of tourism behavior has multiple complexities. Moreover, studies have proved that there is a high correlation between personality traits and tourists' information-related behavior (Stinson *et al.*, 2015), especially in identifying the profiles of individuals that use tourism services (Vallespín *et al.*, 2017). A study related to technology with psychological constructs demonstrated that gender too was found to have a moderating effect between social influence and intention (Tan *et al.*, 2017). With that in mind, we reviewed previous research on personalized recommendations of tourism including, but not limited to: research according to the current location and time of users, tourism recommendation services including scenic spots, hotels, catering and other tourism elements have all been provided to support personalized tourism planning (Yu and Chang, 2009). By using the method of context ordering, a large number of geotagged photos in photo-sharing websites are used to recommend tourist sites (Jiang *et al.*, 2011). SigTur/E-Destination system is adopted to provide personalized recommendation of individual cases for tourist activities in Tarragona (Moreno *et al.*, 2013). By using geographic information technology, a personalized recommendation system based on feature data of scenic spots is designed and implemented to provide users with the most economical travel budget plan (Liu *et al.*, 2015), etc. Then we found that these previous studies relating to the aspects of tourism activities including the six elements of tourism (food, hospitality, traveling, sightseeing, shopping and entertaining) may ignore the personality trait factor in its offerings. This is the research gap that the content of this study wants to discuss with emphasis, by creating user portraits based on user behavior data convergence to locate the user's role from horizontal and vertical dimensions and then carry out effective demand matching.

2. Literature review

2.1 Personalized recommendation

In the 1990s, personalized recommendation was proposed as an independent concept (Hill *et al.*, 1995), and its value is generally defined as"the use of an e-commerce website to provide information and advice to consumers to help them make better decisions Resnick *et al.*, 1997)." Up until now, personalized recommendation is an important technology to actively support personalized products and services in real-time and as a result an increasing number of e-commerce websites are using this technology (Schafer *et al.*, 2001). As a hot research field within computer science, its theoretical algorithm model - the key part of the whole recommendation system has been polished for optimal practicality. The personalized recommendation algorithm model comparison is shown in Table 1. Therefore the technical cost threshold of mainstream model implementation is much lower than before. Generally speaking, the current personalized recommendation algorithm model can be divided into content-based recommendation and collaborative filtering recommendation (Adomavicius and Tuzhilin, 2005). Besides the combination of the above two, more recommendation strategies can be generated to meet users' preferences (Ha, 2002) the comparison of which is shown in Table 1. On the one hand, content-based recommendation from the field of information acquisition and the key to its strategy calculates the similarity between the content characteristics of the recommendation object and the interest characteristics in the user model. Currently, this method is widely used in image recommendation, news recommendation and music recommendation (Vailaya *et al.*, 2001; Kompan and Mária, 2010; Liu, 2013). On the other hand, collaborative filtering recommendation makes recommendations to other users based on

Authors	Algorithm model	Methods used	Findings
Vailaya A., Figueiredo M.A.T, Jain A.K, *et al.*	Content-based	Grouping images into meaningful categories	Show preliminary results for feature reduction using clustering techniques
Kompan M, Mária Bieliková.	Content-based	Cosine-similarity search	Useshort article represent vector to compute similarity between articles in a fast way
Liu N H.	Content-based	Estimation of similarity between content	Proposes a method to calculate a personalized distance measure between different pieces of music based on user preferences
Linden G, Smith B, York J.	Collaborative filtering	Item-to-item collaborative filtering	The algorithm's online computation scales independently of the number of customers and number of items in the product catalog
Herlocker J.L, Konstan J.A, Terveen L.G, *et al.*	Collaborative filtering	From the analysis of various accuracy metrics	Metrics within each equivalency class were strongly correlated, while metrics from different equivalency classes were uncorrelated
Tao Z, Cheung M, She J, *et al.*	Collaborative filtering	Use the operational data from a mobile social game	User-based approach with friendship as similar relationship has better performance than original approach
Yi M, Deng W.	Utility-based	Based on Bayesian networks	It could extend the range of applications for which utility-based recommendation would be more useful
Liang S, Liu Y, JainL, *et al.*	Utility-based	Utility function models	Pay more attention to users' preferences can enhance the recommendation effect
Scholz M, Dormer V, Franz M, *et al.*	Utility-based	Exponential utility functions	Show how retailers can use consumers' willingness to pay estimates for profit-maximizing pricing decisions
Golbeck J.	Social network analysis	Trust in social networks	Show that trust in social networks can make recommendations more accurate than other techniques when the user's opinions about a film are divergent from the average
Liu F, Joo H.	Social network analysis	Collected users' preference ratings data	More accurate prediction algorithms can be produced by incorporating social network information into CF
Sohn J.S, Bae U.B, Chung I.J.	Social network analysis	Using degree of centrality	Provides more appropriate and reliable contents than traditional CRSs and reflects the importance of the role of content creators

Table 1. Personalized recommendation algorithm model comparison

products purchased by users with similar interests, which is the most successful strategy among recommendation strategies, which started to be studied in the 1990s and promoted the growth of the whole recommendation system research. A large number of papers and studies fall into this category (Linden *et al.*, 2003; Herlocker *et al.*, 2004; Tao *et al.*, 2014). For example, the Grundy book recommendation system, Tapestry mail processing system, group lens, Ringo and other recommendation systems all belong to this type of recommendation (Wei *et al.*, 2012). Furthermore, various combinations on these two methods can produce more recommendation results that satisfy more personalized user preferences, such as utility-based recommendations (Yi and Deng, 2009; Liang *et al.*, 2011; Scholz *et al.*, 2015) and social network analysis recommendations (Golbeck, 2006; Liu and Joo, 2010; Sohn *et al.*, 2013).

It should be noted that current recommendation systems use part of the characteristics of the user and the recommendation object when matching the content characteristics of the recommendation object with the user's interests and preferences. The user will only get similar recommendation results as before, and it is difficult to find new information of interest for the user. The main reason is that the acquisition method of users' interests and preferences and the feature extraction method of recommended objects are not very applicable, so it is necessary to introduce more accurate and applicable user and object features. On the other hand, there is a cold start problem when new users appear making it difficult for the system to obtain the user's interest preferences, which cannot be matched with the content characteristics of the recommended object, and it is more difficult for the user to obtain satisfactory recommendation results. In a nutshell, each method has its advantages and disadvantages. The premise and key to constantly improve the models are to find more application scenarios to test and correct. At the same time, it is necessary to consider the volatile environment and the possibility for leveraging the user's cognitive capabilities to avoid the collapse of technical processes (Palanisamy, 2005). So, the current big gap in theory and technology lies in the insufficient diversity of application scenarios, which leads to the insufficient continuous improvement of model technology and its application and transformation ability.

2.2 Personalized recommendation on tourism

Nowadays, the rapidly developed online tourism industry and the increasingly serious phenomenon of information overload has some studies has putting forward opinions that the hedonic dimension of quality is important in adding value for customers (Berbegal-Mirabent *et al.*, 2016). So the personalized recommendation on tourism attract more attention by providing potential travelers with online tourism products that fit their needs and preferences, then further help to make travel decisions more accurately and quickly.

Therefore, the research on the application of personalized recommendation in tourism is beginning to show a sustained increase. Kofler *et al.* focus on the 34,206 tourism photos shared from the Flikr and collected the metadata of each photo, including the title, file name, photo date, uploader and location information, to label the scenic spot and then completed the personalized recommendation by using content-based recommendation technology (Kofler *et al.*, 2011). Hwang *et al.* expressed users' travel preferences with a score vector of h (number of scenic spots) dimension, then constructed a scoring matrix between users and scenic spots, predicted users' rating values by using collaborative filtering recommendation, using the geographical manager to calculate the distance between the user's location and the scenic spots and finally to make recommendations based on the score values and distances comprehensively (Hwang and Yan, 2012). Lorenzi *et al.* proposed a multi-agent recommendation system which including flight recommendation, hotel recommendation and scenic spot recommendation. They based the system on the user input requirements, established the knowledge base, made the knowledge base of each agent self-learning, recorded the user's choices in each interaction to update the knowledge base and then finally generated the combined recommendation, which yielded a useful result utilizing machine learning (Tao and Cheng, 2012). Du S *et al.* proposed a new method of travel path mining that takes the topic hierarchy of scenic spots and the features of scenic spots into consideration and experimental results show that the proposed method can effectively extract the travel route from the mass texts of travel notes (Du *et al.*, 2018).

These studies are still worth pursuing considering the complexity of tourism compared with other ordinary service industries. First of all, the six elements of tourism include food, hospitality, traveling, sightseeing, shopping and entertaining. Each aspect has attributes that lead directly to the complexity of tourism information. Second, on account of tourist activity being a more time-consuming, expensive and risky activity than other common consumer

behaviors, it is constrained by time and consumption expenditure, the number of scenic spots visited by users in a year can be numbered which results in data-sparse characteristics. From this point of view, the application of the traditional collaborative filtering method for personalized tourism recommendation is worth discussing. Third, tourism activities originate from the spiritual needs of potential tourists, which make it difficult for them to accurately express them. Sometimes they cannot even clearly express their motives themselves that well. Besides, due to the influence of factors such as traffic and climate in tourist destinations, their attention to tourism products is extremely unbalanced. In a nutshell, research of personalized recommendation on tourism need a change of perspective from focusing on the simple collection of travel information and the logical speculation of tourism products to focusing on the individual behavior of people- potential travelers. What kind of person is he or she? What kind of preferences does he or she have? What needs might she or he have? The personality trait factor is promising and should be more important than the secondary data available when we make a personalized recommendation on tourism.

According to the above consideration, in this study we want to design a new algorithm, through a picture of the user recommendation: on the one hand, through the tourist attractions' name similarity computes tourist attractions of the user's interest preference; on the other hand user interest spreads to a behavior partition (the same partition attractions may qualify for a tonal), thereby increasing novel recommendation results.

3. A framework design: know you better than yourself

A framework design for the personalized recommendation on tourism is the critical stage in this study and should focus on the unique situation in online tourism and the personality trait factor in its promises. Importantly, it must be reflected in each step of the recommended process. In such a framework design, the tourism activities are involved in the six elements and even the various industrial elements related to tourism.

3.1 Data collection and preprocessing

A complete and comprehensive study based on the perspective of user behavior analysis needs to obtain all behavior records on the website within the user life cycle, and the access channels generally include website data, web server log record data and client user behavior data. The advantages and disadvantages of these three types of user behavior data collection channels are shown in Table 2.

In contrast to the above data collection channels, considering acceptance of the data in this research can be collected and dealt with by adopting the website data as collection channels; online data mainly comes from some special products belonging to one of the famous online tourism sites on January 1, 2019, to June 30, wherein all users of the online behavior generated data. The way to obtain data is to use the crawler program to scan and save the related pages

	Website data	Server logs	Client user behavior data
Advantage	Stable page content Content determinism High accessibility	Complete information recording Convenient to reprocess historical data	Flexible data collection Tracking visitors' movements is more accurate Highly customizable
Disadvantage	High acquisition cost	High acquisition difficulty Unable to capture page specific business information	Low accessibility High technical threshold

Table 2. User behavior data collection channels comparison

of the website as a whole and then to read and parse the key information of the saved webpage HTML format files, followed by saving the key information extracted from these files to the relational database SQL Server for archiving. The data acquisition process is shown in Figure 1.

Among them, the multifunctional crawlers come from various open-source web crawler codes. Using the crawler code can crawl from the website of the original page information for the standard HTML format file. Further, after page parsing, data are drawn from page code attribute information related to user behavior and publicly available web pages about the product name, product price, departure, arrival and the number of days to travel, travel, comment ID, the information such as date, comment and score. To guarantee and improve the effectiveness of the study, this study excluded the tourism product review samples with the number of reviews less than or equal to 10 and the sales volume equal to 0. Measurement for the convenience of the collected primary data statistical analysis, this study collected user explicit data; implicit data information is stored in an essentially a relational database. The total sample size of 500,000 users and 1,579,840 groups of data, according to the actual business scenarios online travel on the data structure design, consists of three categories with a total of 23 attribute information, as shown in Table 3.

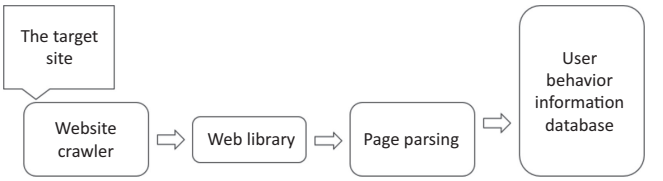

Figure 1.
Data acquisition process

Data categories	Variable
Basic product information	Product_Name
	Product_Price
	Product_Content
	Departure
	Destination
	Travel_Time
	Travel_Days
	Travel_Number
User basic information	User_Id
	Gender
	Age
	Registration_time
	Residential_city
User behavior information	Page_click
	Page_browsing
	Page_dwell time
	Place_order
	Cancel_order
	Payment
	Review_Id
	Review_Time
	Review_Content
	Review_Valence

Table 3.
Data structure

Since real-world data incompleteness and inconsistencies cannot be avoided, direct use of the data will lead to a great deviation of the results. In order to improve the precision performance of creating a user model and ensuring the rationality and efficiency of personalized recommendation, this study needs to preprocess the data acquired. Data preprocessing involves multiple steps. Combined with the actual scenario of this study, the data preprocessing steps adopted include data cleaning, data integration and data conversion.

For example, among the three tourist destinations of "domestic travel", "Japan and South Korea travel" and "Europe and America travel", the observation count of "island travel" in each category is 0, 790 and 210, and the corresponding probability is 0, 0.79 and 0.21. In order to avoid the data error caused by 0 probability events, the Laplace smoothing method was first used to add 1 to the occurrence frequency of "island trip" in each subclass, that is, the total frequency was changed from 1000 to 1003, and then the probability of the three types of island trips was recalculated:

P ("Domestic tour") = 1/1003 = 0.001;

P ("Japan-Korea tour") = 791/1003 = 0.789;

P ("European travel") = 211/1003 = 0.21

The data thus becomes calculable.

3.2 Build product subcategories

Comparative studies are now more mature in an online travel web page setup and information platform. Combined with the previous step integration and transformation of data and considering that online travel products contain multiple segmentation directories and multistage product labels, it is a good choice to follow the top precision design first and proceed downward gradually to rich design principles. To create the online travel products user preference model, you need to build a segmentation directory first, as shown in Table 4.

3.3 Make preference analysis

After the subdivision of online travel products catalog design, the study began to focus on user behavior. On the basis of the above-mentioned user behavior data structure design and the classification standard, user behavior data can be divided into two categories: explicit and implicit. The dominant data are the user's review score of the product. The recessive data includes page click, page browsing and page stop time, order placing, order canceling,

Travel form	Group tour, self-service tour, cruise ship, self-driving tour, destination tour, local play, scenic spot ticket	There are 7 subcategories
Travel topic	Famous mountains and rivers, seaside islands, honeymoon vacation, theme park, wedding photography, heritage tourism, folk experience etc.	There are 7 subcategories
Departure	Beijing, Shanghai, Guangzhou, Wuhan, Changsha. . .	A total of 200+ departure cities
Destination	Category ii: Southeast Asia, South Asia, Thailand, Hong Kong, Macau, Taiwan, Australia, New Zealand, Middle East Africa; Category 3: Sanya, Yunnan, Bali, Maldives. . .	There are 8 secondary categories; 29 popular tertiary categories
Days	1、2、3、4、5、. 20	A total of 20 days can be selected
Price	0–500 yuan; from 500 to 1000 yuan. From 1000 to 2000 yuan. From 2000 to 4000 yuan. From 4000 to 6000 yuan. From 6000 to 10000 yuan. More than 10000 yuan	There are seven price ranges
Season	January, February, . . .December	A total of 12 travel seasons

Table 4. Online travel product catalog

payment, comment ID, comment date and comment content. The user behavior score is calculated, which includes three steps, including correlation analysis, factor analysis and the assignment of user behavior.

To create a complete science of the user preference model, the next step is to subdivide the online travel products information and user behavior, the combination of the user's real-time behavior (product-link click and browsing, etc.) for reading analysis, insight into the real spending intentions of users and also the strength of the reaction according to the strength of the behavior intention, which includes user category preference, user consumption level preference and user geographic location preference.

For example, to predict the preference degree of "John's family" on the tourism product "Hong Kong Disneyland parent-child tour", first of all, the corresponding subdivision directory of "Hong Kong Disneyland parent-child tour" is determined as a "theme park" tourism product; Second, the average score of all overrated tourism products of "John's family" in the subdivided catalog of "theme park" is calculated, as shown in the formula.

$$\overline{x} = \frac{x_1 + x_2 + \ldots + x_n}{n} = \frac{\sum_{i=1}^{n} x_i}{n}$$

Again, this converts the tourism product name keyword vector, expressed by $\overline{\text{vector}}$, according to the formula calculation which in turn yields tourism products "Hong Kong Disneyland parent-child tour" and a corresponding segmentation directory has been made, "John's family," to review all tourism products i meaning the content of the similarity of sim_{ai}, as shown in the formula:

$$\text{sim}_{ai} = \frac{\overline{\text{vector}_i} * \overline{\text{vector}_a}}{|\overline{\text{vector}_i}||\overline{\text{vector}_a}|}$$

where ($\overline{\text{vector}_i}$ means key vector of products i; $\overline{\text{vector}_a}$ means key vector of products a)

Finally, according to formula:

$$\text{Favor\_Ai} = 0.3 \times \overline{X} + 0.7 \times \overline{\text{sim}} \times \overline{X}$$

We calculate the average of the sim_{ai}, and get a score of the "John's family" to predict the "Hong Kong Disneyland parent-child tour". The method of initial conversion of parameter a is equal to $1-a = 0.5$, and a and b factor is the same as the rate of conversion of the a and b, the rate of conversion (the number of times/items being viewed) is adjusted for the a and b. The results are satisfactory when $a = 0.3–0.3–0.3–0 = 0.3–0$ is ideal, so the parameter of a and b is 0.7 and 0.3.

3.4 Sketch out the persona

A user model is a division of users, that is, a fictitious user to represent a user group, and it is a class concept turned into a role. This user model can be more representative than any real individual. The ultimate goal of this user model construction is to reflect an aspect or projection of users in the application field of the online tourism platform. It can include all attribute features related to user behavior and reflect users' value feelings and potential demand for products and services. At the same time, we can perfectly abstract the whole picture of user information according to this model. Of course, the user here refers to the target user who has used and may use a product or service in the future, and the final presentation is a kind of tag system whose purpose is to digitally aggregate and describe real users with tags.

While dividing the dimensions of the user tag system, it should be noted that the weight of each dimension in the tag system is different for different business scenarios. For example, the

"consumption" dimension is a very important indicator in e-commerce products, while it is relatively less important in pure tour products and may not need to be divided into statistics. Therefore, in combination with the actual business situation of this study and based on the attributes of target users of online tourism products and the development direction of product business itself, the portrait of target users' needs to be more fine-grained, so the corresponding weight should be further given after the target users are labeled with subdivision. Thus, the label is an effective expression of the user's interest in the content; the weight is the effective expression of users' interest and preference degree, credibility and probability.

3.5 Personalized recommendation algorithm selection

Considering the online tourism user model and portrait built above, this study has obtained the digital aggregation and description of users in the actual business scenes of online tourism, but there are still practical difficulties before the next step of the personalized recommendation process. First, in the process of classification of online tourism products, manual classification of users and products is required. Subjective factors have a great impact on the generation results, and it is difficult to control the granularity of the segmentation dimensions. Second, when calculating the degree of users' preference and interest in online tourism products, users' comment content data have heterogeneity characteristics, which is difficult to measure quantitatively. Third, different users have different interests and preferences in different situations as to indicate recommendations should be made on the premise of filtering out the differences between historical situations and current situations when using the data of users' historical behaviors.

Based on the above, this study believes that combining the content-based, collaborative filtering and the crypto-semantic model-based recommendation to form a hybrid recommendation scheme, then adding context-aware filtering technology should be more suitable for a personalized recommendation in online tourism. The overall architecture is shown in Figure 2:

4. Conclusion

4.1 Discussion

This study provides an overview of current personalized recommendation research progress and points out that the key to constantly improve the models is to find more application scenarios to test and correct. Especially in online tourism, the personalized recommendation needs a change of perspective from focusing on the simple collection of travel information and the logical speculation of tourism products to focusing on the individual behavior of people who are potential travelers. Finally, the overall recommendation process of this study includes five steps: Data collection and preprocessing; Build product subcategories; Make preference analysis; Sketch out the persona; personalized recommendation algorithm selection. This recommendation may know you better than you know yourself.

According to the framework of the online tourism personalized recommendation in this study, the individual recommendation method is adopted as the main approach to enhance customer stickiness and improve the transformation efficiency of tourism products from online to offline, then put forward the directional strategy recommendations to the future operation and management of the online tourism enterprise: which is to put emphasis on user value assessment and strengthen the personalized precision marketing.

4.2 Implications

Based on the above research logic, content and process, this research has a few implications. On the theoretical side,they are:

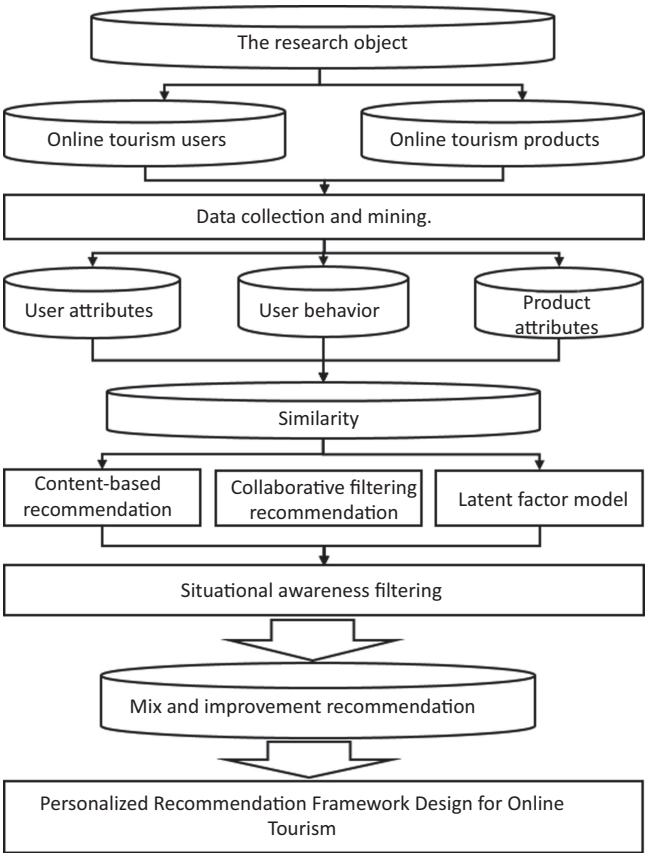

Figure 2.
An overall architecture

(1) Establishes the logical space of "gathering user needs and reverse customization" between the online design and supply of tourism products;

(2) Put forward and emphasize the importance of the personality trait factor in tourism personalized recommendation;

On the practical side, the findings offer valuable insight to managerial and policy makers, which are:

(1) Clarifies concepts for better implementation of the technical operation including online tourism user behavior and generated data, user preference theme and space, user model and user's image, user-product two-dimensional matrix, etc.;

(2) Through the description and explanation of concepts related to personal characteristics, emphasis in online tourism, the personalized recommendation needs a change of perspective from focusing on the simple collection of travel information and the logical speculation of tourism products to focusing on the individual behavior of people who are potential travelers;

(3) Give some technical improvement strategies including creating user portrait based on behavior data convergence to locate the user's role from horizontal and vertical

dimensions and also clear the logical levels and association among them, verifies the similarity measurement and calculation and optimizes the implementation of the personalized recommendation program under online tourism business scenarios.

5. Limitations and future research

One of the limitations of this study is that it only applies the model to improve the logical path of the personalized recommendation process of online tourism. It does not focus on the mobile e-commerce environment of online tourism. How to consider the functional characteristics of a mobile database at the same time, as well as how to ensure that consumers can enjoy the satisfaction of travel products and services anytime and anywhere, still need further work. Second, our system and paper only designs and describes the framework of the online tourism personalized recommendation and we only compared our framework advantages with other single recommendations. Future studies can also generate the results from the actual use of the enterprise and compare this with results obtained from other models again to drive continuous improvement based on practice. Further, the research can deeply explore and build a theoretical framework about "personality trait" to improve the operability of the framework design more specifically and easy to operate. Lastly, the framework would be greatly improved if we not only put emphasis on just user value assessment and strengthened the personalized precision marketing, but also made some recommendations to help enterprises recreate their business value. This involves a decision-support system feature and needs further working.

References

Adomavicius, G. and Tuzhilin, A. (2005), "Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions", *IEEE Trans on Knowledge and Data Engingeering*, Vol. 17 No. 6, pp. 734-749.

Ardissono, L., Gena, C., Torasso, P., *et al.* (2003), "Personalized recommendation of TV programs", [C]// AI*IA 2003: advances in artificial intelligence, *8th Congress of The Italian Association For Artificial Intelligence*, Pisa, Italy, September 23-26, 2003, Proceedings.

Berbegal-Mirabent, J., Mas-Machuca, M. and Marimon, F. (2016), "Antecedents of online purchasing behaviour in the tourism sector", *Industrial Management and Data Systems*, Vol. 116 No. 1, pp. 87-102.

Du, S., Zhang, H., Xu, H., *et al.* (2018), "To make the travel healthier: a new tourism personalized route recommendation algorithm", *Journal of Ambient Intelligence and Humanized Computing*.

Golbeck, J. (2006) "Generating predictive movie recommendations from trust in social networks", *Proceedings of the Fourth International Conference on Trust Management*.

Guoxia, W. (2012), "Survey of personalized recommendation system", *Computer Engineering and Applications*.

Ha, S.H. (2002), "Helping online customers decide through Web personalization", *Intelligent Systems, IEEE*, Vol. 17 No. 6, pp. 34-43.

Herlocker, J.L., Konstan, J.A., Terveen, L.G., *et al.* (2004), "Evaluating collaborative filtering recommender systems", *ACM Transactions on Information Systems*, Vol. 22 No. 1, pp. 5-53.

Hill, W., Stead, L., Rosenstein, M., *et al.* (1995), "Recommending and evaluating choices in avirtual community of use", *Conference on Computer Human Interaction*, ACM Press, NewYork, NY, pp. 194-201.

Huang, Y. and Bian, L. (2009), "A Bayesian network and analytic hierarchy process based personalized recommendations for tourist attractions over the internet", *Expert Systems with Applications*, Vol. 36 No. 1, pp. 933-943.

Hwang, S. and Yan, W. (2012), "On-tour attraction recommendation in a mobile environment", *IEEE International Conference on Pervasive Computing and Communications*, IEEE Press, New Jersey, NJ, pp. 661-666.

Jasmina, Berbegal-Mirabent, M. *et al.* (1980), "Antecedents of online purchasing behaviour in the tourism sector", *Industrial Management and Data Systems*.

Jiang, K., Wang, P. and Yu, N. (2011), "Context rank: personalized tourism recommendation by exploiting context information of geotagged web photos", *2011 Sixth International Conference on Image And Graphics (ICIG)*", IEEE Computer Society.

Jiawei, H. and Micheline, K. (2006), "Data mining: concepts and techniques", *Data Mining Concepts Models Methods and Algorithms Second Edition*, Vol. 5 No. 4, pp. 1-18.

Kim, H.K., Kim, J.K. and Ryu, Y.U. (2009), "Personalized recommendation over a customer network for ubiquitous shopping", *IEEE Transactions on Services Computing*, Vol. 2 No. 2, pp. 140-151.

Kofler, C., Caballero, L., Menendez, M., *et al.* (2011), "Near2me: an authentic and personalized social media-based recommender for travel destinations", *The 3rd ACM SIGMM International Workshop on Social Media*, ACM Press, New York, NY, pp. 47-52.

Kompan, M. and Mária, B. (2010), "Content-based news recommendation", *11th International Conference E-Commerce and Web Technologies, EC-Web 2010*, Bilbao, Spain, September 1-3, 2010, DBLP, Proceedings.

Liang, S., Liu, Y., Jian, L., *et al.* (2011), "A utility-based recommendation approach for academic literatures", *2011 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (Wi-Iat)*, ACM.

Linden, G., Smith, B. and York, J. (2003), "Amazon.Com recommendations: item-to-item collaborative filtering", *IEEE Internet Computing*, Vol. 7 No. 1, pp. 76-80.

Liu, N.H. (2013), "Comparison of content-based music recommendation using different distance estimation methods", *Applied Intelligence*, Vol. 38 No. 2, pp. 160-174.

Liu, F. and Joo, H. (2010), "Use of social network information to enhance collaborative filtering performance", *Expert Systems with Applications*, Vol. 37 No. 7, pp. 4772-4778.

Liu, D.R., Tsai, P.Y. and Chiu, P.H. (2011), "Personalized recommendation of popular blog articles for mobile applications", *Information Sciences*, Vol. 181 No. 9, pp. 1552-1572.

Liu, H.L., Li, J.H. and Peng, J. (2015), "A novel recommendation system for the personalized smart tourism route: design and implementation", *2015 IEEE 14th International Conference on Cognitive Informatics and Cognitive Computing (ICCI*CC)*, IEEE.

Moreno, A, Valls, A., Isern, D., *et al.* (2013), "SigTur/E-destination: Ontology-based personalized recommendation of tourism and leisure activities", *Engineering Applications of Artificial Intelligence*, Vol. 26 No. 1, pp. 633-651.

Oliveira, T. and Martins, M.F. (2010), "Understanding e-business adoption across industries in European countries", *Industrial Management and Data Systems*, Vol. 110 Nos 8-9, pp. 1337-1354.

Palanisamy, R. (2005), "Strategic information systems planning model for building flexibility and success", *Industrial Management and Data Systems*, Vol. 105 Nos 1-219, pp. 63-81.

Pazzani, M.J. (1999), "A framework for collaborative, content-based and demographic filtering", *Artificial Intelligence Review*, Vol. 13 Nos 5-6, pp. 393-408.

Resnick, P. and Varian, H.R. (1997), "Recommender systems", *Communications of the ACM*, Vol. 40 No. 3, pp. 56-58.

Schafer, J.B., Konstan, J.A. and Riedl, J. (2001), "E-commerce recommendation applications", *Data Mining and Knowledge Discovery*, Vol. 5 Nos 1-2, pp. 115-153.

Scholz, M., Dorner, V., Franz, M., *et al.* (2015), "Measuring consumers' willingness to pay with utility-based recommendation systems", *Decision Support Systems*, Vol. 72, pp. 60-71.

Sohn, J.S., Bae, U.B. and Chung, I.J. (2013), "Contents recommendation method using social network analysis", *Wireless Personal Communications*, Vol. 73 No. 4, pp. 1529-1546.

Shih, T.K., Chiu, C.F., Hsu, H.H., *et al.* (2002), "An integrated framework for recommendation systems in e-commerce", *Industrial Management and Data Systems*, Vol. 102 Nos 8-9, pp. 417-431.

Stinson, J.L., Matsuura, Y. and Kahle, L.R. (2015), "Personality and personal values in travel destination", *Assessing the Different Roles of Marketing Theory and Practice in the Jaws of Economic Uncertainty*, Springer International Publishing.

Tan, W.H., Lee, V.H., Lin, B., *et al.* (2017), "Mobile applications in tourism: the future of the tourism industry?", *Industrial Management and Data Systems*, Vol. 117 No. 3, pp. 560-581.

Tao, Y. and Cheng, D. (2012), "Research on personalized tour service system", *International Conference on Information Management*, IEEE.

Tao, Z., Cheung, M., She, J., *et al.* (2014), "Item recommendation using collaborative filtering in mobile social games: a case study", *IEEE Fourth International Conference on Big Data and Cloud Computing*, IEEE Computer Society.

Vailaya, A., Figueiredo, M.A.T., Jain, A.K., *et al.* (2001), "Image classification for content-based indexing", *IEEE Transactions on Image Processing*.

Vallespín, M., Molinillo, S. and Mu?Oz-Leiva, F. (2017), "Segmentation and explanation of smartphone use for travel planning based on socio-demographic and behavioral variables", *Industrial Management and Data Systems*, Vol. 117 No. 3, pp. 605-619.

Wei, S., Ye, N., Zhang, S., *et al.* (2012), "Item-based collaborative filtering recommendation algorithm combining item category with interestingness measure", *International Conference on Computer Science and Service System*, IEEE.

Yi, M. and Deng, W. (2009), "A utility-based recommendation approach for E-commerce websites based on bayesian networks", Business Intelligence: Artificial Intelligence In Business, Industry And Engineering", *Proceedings of the Second International Conference on Business Intelligence and Financial Engineering, BIFE 2009*, Beijing, China, 24-26 July 2009, IEEE.

YinC, X., Guo, Y., Yang, J.G. and Ren, X. (2018), "A new recommendation system on the basis of consumer initiative decision based on an associative classification approach", *Industrial Management and Data Systems*, Vol. 118 No. 1, pp. 188-203.

Yu, C.C. and Chang, H.P. (2009), "Personalized location-based recommendation services for tour planning in mobile tourism applications", *E-Commerce and Web Technologies, 10th International Conference, EC-Web 2009, Linz*, Austria, September 1-4, 2009, Springer, Berlin Heidelberg, Proceedings.

Corresponding author
Xiaoqian Wang can be contacted at: wangxiaoqian701@126.com