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A User-POI-Guide Cost Optimization Method for Tourism Planning Considering Social Distance and User Preferences

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Abstract

MaaS (Mobility as a Service) itself has come into common use, and these developments have attracted keen interest from the industry in recent years. MaaS can be applied as a solution to deal with the current situation by considering the social distance. However, due to the time-share mechanism, personal assets are monopolized by specific users for a long time that cannot be shared with other users at the same time. Thus, the sharing economy companies in the tourism industry (e.g., Airbnb Experience and Huber) are in a dilemma of low productivity and high cost. In this research, we propose a new travel guide sharing service that considers the concept of social distance and user preferences. The user side only needs to select simple conditions such as travel time and the number of POIs (Point of Interest) that she/he plans to visit, meanwhile, the guide side simply inputs the POIs that she/he can guide. Furthermore, by analyzing these basic information, our proposed system can recommend the tour guides, scenic spots, and route planning to provide a real-time tour guide plan, which addressed the user's preferences and reduced the face-to-face communication to users in advance. To verify the effectiveness of our proposed method, we also ask 68 users to evaluate our system and analyze the results of questionnaires.

Keywords: travel guide planning, recommendation system, social distance, user preferences, COVID-19

1. Introduction

Since 2019, the COVID-19 outbreak has put the whole world in an unprecedented difficult situation bringing life around the world to a frightening halt and claiming thousands of lives (Jamshidi et al., 2020). On March 9, 2020, Japanese medical experts refined their definition of a high-risk environment as a place with the overlapping "three Cs" (three close-contact situations): 1) closed spaces with poor ventilation; 2) crowded places with many people nearby; and 3) close-contact settings such as close-range conversations[1]. Because the risks of virus spread can be minimized by avoiding physical contact among people, the way we socialize around the world is changing dramatically with the measures to avoid the three Cs and to take social distance. Thanks to telework infrastructure, people can use IoT platform-based mobile terminals to communicate with each other without any physical contact (Ganichev and Koshovets, 2021).

On the other hand, in the tourism, education, medical, and other fields, there are many restrictions on providing all services remotely. It has caused huge economic losses, especially in the Japanese tourism industry (Kabadayi et al., 2020; Alashhab et al., 2021). MaaS (Mobility as a Service) provides a seamless passenger experience using multiple modes of transport from the beginning until the end of a journey, and its developments have attracted keen interest from the industry in recent years (Christiaanse, 2019; Hensher et al., 2020). MaaS can be applied as a solution to deal with the current situation by considering the social distance (Bothos et al., 2019; Georgakis et al., 2019). The service of MaaS is an important foundation of the sharing economy service (Barron et al., 2018; Jiang et al., 2018), which can share assets (and human assets) in real-time. Sharing economy represents activities between people to obtain, provide, or share access to goods and services, coordinated by online services (Lecuyer et al., 2017). However, due to the time-share

[1] https://www.mhlw.go.jp

URI: https://hdl.handle.net/10125/103245
978-0-9981331-6-4

mechanism, personal assets are monopolized by specific users for a long time that cannot be shared with other users at the same time. Thus, the sharing economy companies in the tourism industry (e.g., Airbnb[2] and Huber[3]) are in a dilemma of low productivity and high cost (Dredge and Gyimóthy, 2015).

In this study, to fill the gap described above, we propose a new travel guide sharing service considering the concept of social distance. The user side only needs to select simple conditions such as travel time and the number of POIs (Point of Interest, a specific physical location which someone may find interesting) that she/he plans to visit, meanwhile the guide side simply inputs the POIs that she/he can guide (e.g., guide time and language). By analyzing these basic information, our proposed system can recommend the tour guides, scenic spots, and route planning to provide a real-time tour guide plan, which addressed the user's preferences and reduced the face-to-face communication to users in advance.

Overall, our main contributions are as follows:

- In response to the situation in the post-COVID-19 era, we proposed a new travel guide sharing service that considers social distance. In this study, we defined the "social distance" as "the number of participants" and "degree of congestion" (detailed in Section 4.2).

- Our proposed system can recommend the tour guides, scenic spots, and route planning to provide a real-time tour guide plan, which addressed user's preferences and reduced the face-to-face communication to users in advance.

- The experiment results showed that based on spatio-temporal constraints of guides and users, our proposed cost optimization method can also recommend the multiple attractions and guides, and supply the suggested route with the minimum cost according to the number of attractions specified by users.

The remainder of this paper is structured as follows. In Section 2, we discuss previous research which has been carried out related to the sharing economy and user review analysis. Afterward, in Section 3, we provide an overview of our proposed tourism guide planning recommendation system. In section 4, we describe the proposed high-performance optimization method based on characteristics of POIs, users, and guides. Section 5 shows our implemented tourism planning system. Section 6 evaluates and discusses our proposed optimization method. Finally, in Section 7, we conclude this study and discuss future works.

2. Related Work

In this section, we introduce the related research of sharing economy and guide matching. And we also describe the differences between previous methods and our proposed methods.

The growth of the sharing economy is driven by the emergence of platforms such as Uber[4] and Lyft[5] (Hossain, 2020). They play a significant role in hospitality and travel, and their businesses have been impacted around the world due to COVID-19 (Hossain, 2021). In their research (Fang et al., 2017), Fang et al. focused on the design of prices and subsidies in sharing platforms. Their results provided insights into the trade-off between revenue-maximizing prices and social welfare maximizing prices. So et al. focus on peer-to-peer accommodation services in the sharing economy (So et al., 2019). Their results indicated that social distance negatively affects guest loyalty toward the listing hosts, while spatial distance has a positive influence on guest loyalty.

Through the analysis of the phenomenon of shared bikes, Yang and Bo explored the development of a sharing economy in China (Shuai and Qibo, 2018). They analyzed the internal relationship between sharing bicycles and sharing economy. After that, they pointed out the problems in the sharing bicycles operation's development and the sharing economy and put forward some related countermeasures. In the article of (Thebault-Spieker et al., 2017), the authors investigated how key principles from in sharing economy platforms. In addition to highlighting systemic sharing economy biases, they more fundamentally demonstrated the importance of considering well-known geographic principles when designing and studying sharing economy platforms. In another study, Tedjasaputra and Sari pointed out that sharing economy has created several opportunities for Smart Cities and their communities around the world to create a better and smarter working and living environment (Tedjasaputra and Sari, 2016). With economic transactions that usually happen through a variety of interconnected data-driven digital platforms, sharing economy has the potential to improve asset utilization and reduce transaction cost or waste effectively and efficiently.

Online reviews provide consumers with valuable

[2]https://www.airbnb.jp/
[3]https://huber.co.jp/
[4]https://www.uber.com/
[5]https://www.lyft.com/

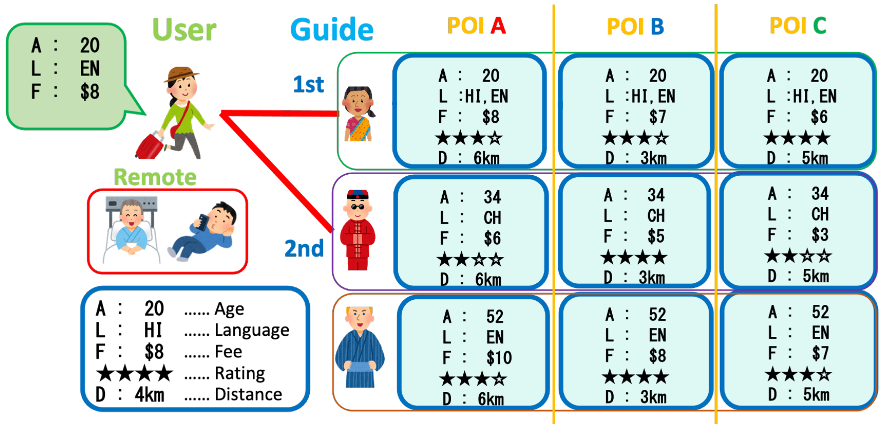


Figure 1. Tourism guide planning based on multiple POIs and multiple guides.

information that guides their decisions on a variety of fronts. Although the proliferation of online reviews gives insights about different aspects of a product, it can also prove a serious drawback: consumers cannot and will not read thousands of reviews before making a purchase decision. This always needs to extract useful information from large review corpora has spawned considerable prior work (Mudambi and Schuff, 2010). However, Lappas et al. noticed that review summarization sacrifices the immediacy and narrative structure of reviews (Lappas et al., 2012). Likewise, review selection leads to redundant or non-representative summaries. As a solution, they filled the gap between existing review-summarization and review-selection methods by selecting a small subset of reviews that together preserve the statistical properties of the entire review corpus. Nowadays, online shopping is increasingly becoming people's first choice when shopping (Singh et al., 2017), it is the common sense of users to comment on e-commerce sites represented by Amazon[6] and Rakuten[7]. With the popularity of these e-commerce sites, there is a lot of analysis and research based on user comments (Noor et al., 2019; Chehal et al., 2021). Santos et al. collected reviews from two sharing economy platforms, Airbnb and Couchsurfing[8], and from one platform of the formal economy that works mostly with hotels, Booking.com[9], for some cities in the United States and Brazil (Santos et al., 2018). They performed a sentiment analysis in the shared texts and found that reviews in the sharing economy tend to be more favorable than those in the formal economy.

To sum up, we listed the previous research on sharing economy platforms and social/economic benefits. However, these research objects were "things" represented by sharing, which has not touched the sharing of "human assets". The difference of this study is that we propose a travel guide (human and knowledge) sharing method among multiple users to realize the sharing of human assets in the context of mobility and tourism.

[6]https://www.amazon.co.jp/
[7]https://www.rakuten.co.jp/
[8]https://www.couchsurfing.com/
[9]https://www.booking.com/

3. Overview of Tourism Guide Planning Recommendation System

Figure 1 shows an overview of our tour guide planning recommendation system. To share the human assets of POI with a high degree of satisfaction, based on the guide's knowledge and user preferences, our proposed method is a system to optimize ranking and multiple matches POI and guide and other participants. In this study, we originally utilized "language", "fee", "rating (comments of guide)", "distance" and other variables to optimize the cost for tourism planning (more details are shown in Section 4.2). At the current stage, we didn't use the "age" variable, which is shown in Figure 1, and we plan to consider more variables for cost optimization in the future.

Specifically, In the matching of users and guides, the guide side needs to input the POIs information that she/he can guide (e.g., guide time, fee, and language), meanwhile, the user side only needs to select simple conditions such as travel time, language, and the information of POIs that she/he plans to visit. It is also possible to recommend multiple spots and guides. In the matching between users, firstly, we analyzed the text content of user reviews and calculated the degree of association between reviews by collaborative filtering. Secondly, we calculated the similarity of the feature vectors to obtain the similarity between users. In particular, we focus on the matching between the

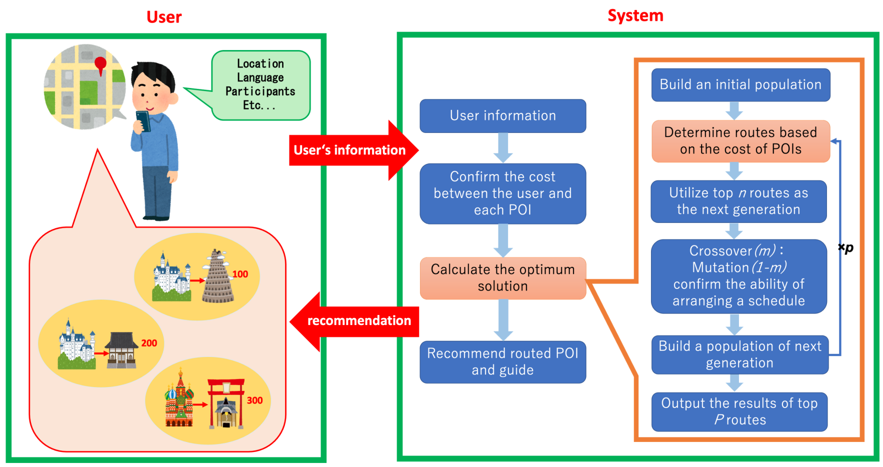


Figure 2. The flow of our recommendation system.

user and different guides in different POIs and represent the optimization method for recommending the POIs, and guides in the optimum route which considers the physical distance from users to the information registered on POIs by guides.

4. Optimization Method based on Characteristics of POI - User - Guide

In this section, we define the user characteristics (preferences) and the travel guide characteristics in our guide planning recommendation system and introduce the methods of recommending travel guides to users based on these characteristics.

Our proposed recommendation system flow is shown in Figure 2. In this system, users first input the start time and the number of participants. Then, the system receives the information and calculates the distance and time cost of each guide data according to the information that the guides had registered in the system. Based on minimizing the total cost, the route of POI and the guide are recommended. For example, if two places are selected from the five POIs: A, B, C, D, and E for route recommendation, route: A $\rightarrow$ B is recommended as the optimum planning result because the cost of A $\rightarrow$ B: is the minimal in all routes. In the above optimization process, after investigating whether the schedule of the candidate guides meets the travel time set by users. The route is then determined. After that, the cost of the distance between the determined routes is added in the next process.

4.1. Cost Factors of POI - User - Guide

In the matching process, the following information is registered by guides and users.

- Guide registration information: POI information (possible to guide), date and time, guide time, fee, language, comments on POIs
- User registration information: POI information (want to visit), date and time, guide time, fee, language, review

The reviews are evaluated by a Likert scale (Joshi et al., 2015) through the information registered after guidance. The matching between users is based on user review sentences, except for spatio-temporal matching. We extract feature words from reviews and calculate cosine similarities (Singhal et al., 2001) using these feature vectors. In addition to the space-time matching such as place and time, user comments are also used for the user-to-user matching. Feature words are extracted by comment analysis, and cosine similarity is calculated by using these feature vectors.

It is desirable to have a lot of knowledge about POIs to realize a guide with a high degree of satisfaction. Therefore, in this study, the knowledge of POIs is used as a guide characteristic to measure how much the guide knows about the POIs.

To extract the knowledge of the guide, firstly, we extract the "comments on POIs" part which is registered in the guide sharing system. Secondly, we extract the feature words by *TF-IDF* (Ramos, 2003), and utilize the word embedding tool Word2Vec (Mikolov et al., 2013) for acquiring word vectors.

4.2. Cost Optimization based on Distances and Characteristics

In this section, we describe the optimization elements and techniques for recommending multiple guides (POIs) within the user's desired time.

Table 1. Examples of cost functions.

ID	area	start time	finish time	time cost	evaluation
User	Nijo Castle	11:00	17:00	-	-
Guide A	Nijo Castle	10:00	17:00	90 min	77
Guide B	Nijo Castle	9:00	12:00	60 min	77
Guide C	Nishiki Tenmangu Shrine	12:30	16:00	90 min	60

Furthermore, in this study, we assumed that "keeping social distance" needs to consider two indicators: "the number of participants" and "degree of congestion". Thus, by adding the "distance between POIs", the final "distance" which we should calculate is defined as "the number of participants", "degree of congestion" and "distance between POIs", more details of the cost optimization method are shown as follows.

Firstly, the elements of cost function creation are shown as follows:

- **distance** 1: distance between POIs, 2: the number of participants, 3: degree of congestion
- **time** 1: guide start time, 2: guide end time
- **price** 1: participation fee
- **semantic** 1: language, 2: comments on POIs, 3: comments on guide, 4: similarity with other users

We use these elements to calculate the cost of "distance from POI" as $Cost_D$, when ΔD is the distance between user and POIs. The variables of lat_U and lat_G denote the latitudes, and $long_U$ and $long_G$ denote the longitudes of user and goal. (C_d, C_p, C_c, C_t, C_v, C_m, and C_s are set as constants.)

$$Cost_D = \Delta D * C_d \quad (1)$$

$$\Delta D = \sqrt{(lat_U - lat_G)^2 + (long_U - long_G)^2} \quad (2)$$

Then, we calculate the cost of the "number of participants" as $Cost_P$ by the following formula. When the variable of POI_{area} is the area of POI, $population$ is the number of people in POI predicted from the number of tweets, $users_{local}$ is defined as the number of participants.

$$Cost_P = POI_{area}/(population + users_{local}) * C_p \quad (3)$$

For the "degree of congestion" $Cost_C$, we apply congestion information C_c acquired from Google Maps.

$$Cost_C = congestion * C_c \quad (4)$$

When it comes to cost of time $Cost_T$, guide side are $start_G, end_G$, user side are $start_U, end_u$.

$$Cost_T = (|start_U - start_G| + |end_U - end_G|) * C_t \quad (5)$$

In the cost of price $Cost_V$, $value$ is defined as price setting from users.

$$Cost_V = (value/users_{local}) * C_v \quad (6)$$

The cost of "language" is set as 0 if the language entered by each guide matches the language specified by the local (remote) user. In contrast, we add a constant C_m if there is no match of the language specified by the local (remote) user and each guide.

In the part of "semantic", we calculate the similarity between the local or remote user and each POI based on the similarities of the user's preference and the semantic distance using the cosine similarity as described in Section 4.1, and multiply a constant C_s by subtracting the similarity from 1 as follows:

$$(1 - similarity) * C_s \quad (7)$$

$$\begin{aligned} similarity &= \textit{user preference} + \textit{semantic distance} \\ &= cos(V_P, V_U) + cos(V_{P_{loc}}, V_{U_{loc}}) \quad (8) \end{aligned}$$

where $cos(V_P, V_U)$ denotes the similarity of the user's preference using the cosine similarity between each POI vector V_P and the user vector V_U. $cos(V_{P_{loc}}, V_{U_{loc}})$ denotes the similarity of the semantic distance using the cosine similarity between the vector of each POI's location $V_{P_{loc}}$ and the vector of the user's location $V_{U_{loc}}$.

Finally, the cost function in our guide sharing system is determined by using the above calculated results. Table 1 showed the terms which are utilized as variables in determining cost functions.

In the "area" column, if it is "guide", it means POI information which is input by guides in advance. If it is "user", there are two situations: 1) If the area has been input by the user in advance, it also indicates the name of the POI; 2) If not, we use the above formula to calculate the cost of the distance between the user and the guide. The "evaluation" is the rating scores of the POI rated after guidance to calculate the knowledge level of guides.

In order to minimize cost in the above cost function, we applied random search (Solis and Wets, 1981) and genetic algorithm (Whitley, 1994) as the optimization methods in this study.

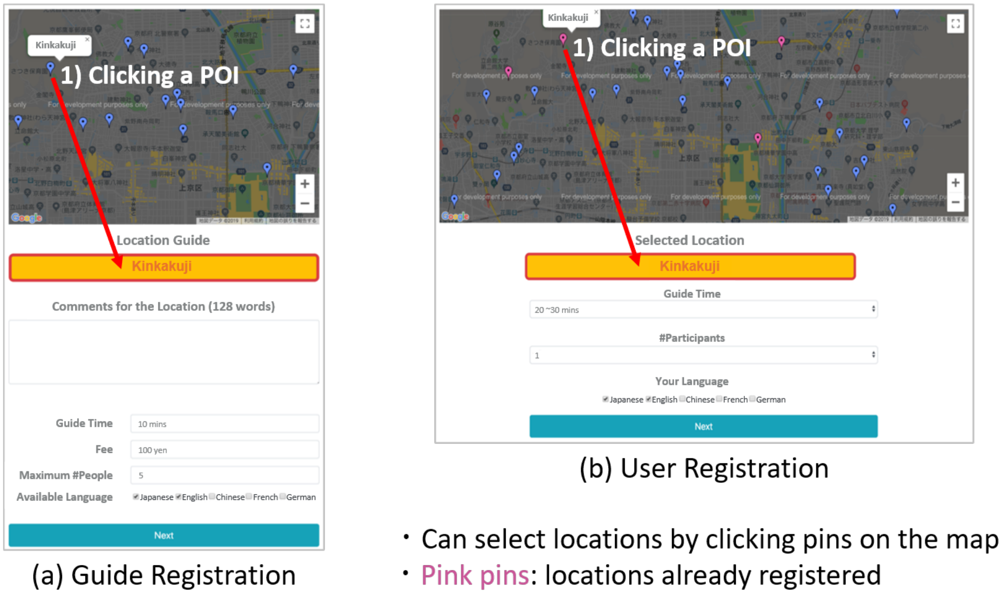


Figure 3. Guide and user registration.

4.3. Random Search

The random search algorithm is useful for many ill-structured global optimization problems with continuous and/or discrete variables (Zabinsky, 2010). It replaces the exhaustive enumeration of all combinations by selecting them randomly.

In this study, random search is utilized as a method of random predicting by n times for examining the cost and selecting the best prediction in it.

1. Initialize algorithm parameters, then generate initial points and calculate costs.
2. Compare the value to the cost of (1), select the smaller one.
3. Update parameters and iterate (1) & (2) steps by n times.
4. The final value is displayed as result.

4.4. Genetic Algorithm

A genetic algorithm is a stochastic search-based optimization algorithm based on principles of genetics and natural selection between individuals for appropriating limited natural sources. The success of the winner normally depends on their genes, and reproduction by such individuals causes the spread of their genes. By successive selection of superior individuals and reproducing them, the population will be led to one that can obtain more natural resources. The genetic algorithm simulates this process and calculates the optimum of objective functions. In this study, we applied a genetic algorithm by the following steps:

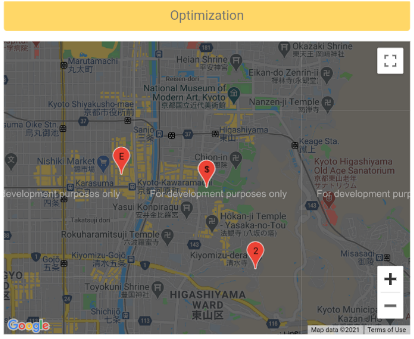
1. Create the initial population.

   Afterward, we add the cost to each result according to the total distance.
2. Extract Top 10 to the next generation.
3. Crossover and mutation operators.

   Firstly, we need to check whether the schedule can meet the guide start time. In this process, we count t minutes to the total distance for considering transportation. Secondly, we add the cost to each result according to the total distance.
4. Generate the next generation population.
5. Output the top 3 results.

Where a new population contains some of the best solutions, we extract them by mutating and crossover steps. The mutation is a modification method in which small and simple changes are randomly added to an existing solution, and the crossover is a modification method in which two superior solutions are extracted and a new solution is created in some way.

In our previous research (Shibata et al., 2020), we assigned several optimization methods to minimize the cost, and we found that the genetic algorithm achieved the best performance in our system.



1st :	Yasaka Shrine	
2nd :	Kiyomizu-dera	
End :	Nishiki-Tenmangu Shrine	
location	locationYasaka Shrine	locationKiyomizu-dera
latlng	lat35.0036 , long135.779	lat34.9948 , long135.785
max_num_participant	max_num_participant5	max_num_participant5
charge	charge100	charge200
scheduleGID	scheduleGID1183	scheduleGID1189
GID	GIDgest01	GIDguide02
year	year2019	year2019
date	date11-30	date11-30
start_time	start_time08:00:00	start_time08:00:00
end_time	end_time18:00:00	end_time17:00:00

Figure 4. The results of guide planning recommendation.

5. System implementation

For implementing our tourism guide planning recommendation system[10], our experiment environment is set up as follows: Apache 2.4.29, Flask 1.1.2, Python 3.6.9, PHP 7.2.24, and MySQL 14.14.

According to preliminary experiments (Shibata et al., 2020), the parameters of genetic algorithm used in our system are set as follows:

- Population size is 50;
- The number of individuals which passed to next generations is 10;
- The ratio of mutation and crossover is 6:4;
- The number of generation is 25.

5.1. Guide and User Registration

Figure 3 (a) showed the registration interface of the guide side. After the system displays POIs on the map, guides are required to register her/his information of POI information (possible to guide), date and time, guide time, fee, language, comments on POIs. Then, if a user made a reservation, the user's information can be viewed on the reservation confirmation interface.

Figure 3 (b) showed the registration interface of the local (remote) user side. Users are required to register her/his information of POI information (that they want to visit), date and time, guide time, fee, language. Then, users can select a guide that meets those conditions from our recommended results.

[10] https://delab2.kyoto-su.ac.jp/guidesharing/top.html

5.2. Guide and POI Recommendation

As a solution for omitting the trouble of entering the desired location and date, our system obtains the current location information from the local user's mobile device and presents tourism POIs. The tourism POIs mentioned above are 20 POIs within a one-mile radius of the acquired current location recommended through our system. Afterward, our system can perform a quick recommendation to present POIs in the limited area. For the selected POIs, our system can recommend a guide for selected POI within a certain time based on the current time. Moreover, users can search nearby POIs and obtain guide information matching by our system.

After users input their information and select the number of places that they plan to visit, the planning result, the same number of places are plotted on the map as shown in Figure 4.

6. Evaluation

In this section, we evaluate the performance of our tourism planning system implemented in Section 5.

6.1. Setting and Evaluation Method

In the experiment, we randomly selected 24 POIs in Kyoto (Japan) from the travel agency data set. Due to the influence of COVID-19, it was difficult to collect tour guide data. Thus, we registered several pseudo guides and evaluated the tourism planning based on these guides and POIs information.

Firstly, POI data consist of four columns: POI name, category of shrine/park, latitude and longitude, and URL. Secondly, the pseudo-guide data were set as 10 columns: ID, guide date, start and end time, language, POI name, latitude and longitude, maximum participation number, fee, time, and reviews of guidance. Finally, for these POI and guides, we asked 68 users to evaluate the proposed planning system based on the cost function proposed in Section 4.2.

To verify the effectiveness of our proposed method, we utilized a five-point Likert scale (1 to 5) in the following four evaluation (Q1, Q2, Q3, and Q4) items

Table 2. Mean and standard deviation of the questionnaire results.

	Mean		standard deviation	
	Baseline	Proposed	Baseline	Proposed
Q1	2.941	**3.397**	0.784	**0.667**
Q2	4.235	**4.324**	0.689	**0.629**
Q3	3.103	**3.529**	0.942	**0.737**
Q4	3.25	**3.456**	0.864	**0.794**
Average	3.382	**3.676**	0.967	**0.803**

to evaluate the guide planning system that implemented the optimization method. Q5 asks users to answer the number of recommended POIs that she/he would like to visit. As a comparison of optimization methods, we compared the results of the random search (baseline) and genetic algorithm (proposed method). The bigger the number, the higher the evaluation on the 5-stage. All five evaluation items are set as follows:

Q1 Compared with the plan made by yourself, how do you think about the recommended plan?

Q2 Compared with making a plan by yourself, is the recommended plan easier (faster)?

Q3 How do you think the appropriateness of the total traveling distance is recommended by the planning results displayed on the map?

Q4 How would you rate the appropriateness of the recommended POI order?

Q5 How many of the recommended POIs would you like to visit?

To reduce the effect by the condition of choice in the experiment, as the initial setting, we set the number of recommended POIs as three, the start time as 9 a.m., the end time as 12 a.m., the participant as one person, language as Japanese, and the starting place as Karasuma Oike station. Furthermore, the personal information of 68 subjects are the 20s to 50s Japanese native speakers.

6.2. Results of Questionnaires

The results of the questionnaires are shown in Figure 5, Figure 6, and Table 2. The bigger the number, the higher the evaluation. In Figure 5, Q1_B, Q2_B, Q3_B and Q4_B mean the results which are optimized by baseline, Q1_P, Q2_P, Q3_P and Q4_P are the results which are optimized by the proposed method.

In the questionnaire survey results, we set "extremely good" as 5, and "extremely bad" as 1. The t-tests were carried out on the results of the proposed and baseline method from Q1 to Q5. We found that there are significant differences between the proposed and baseline method in Q1 and Q3, and the proposed method achieved better performance than baseline from Q1 ($p < 0.05$). The mean and standard deviation of the proposed and baseline method are shown in Table 2. Each result from Q1 to Q4 of the proposed method obtained a higher mean and lower standard deviation than baseline, which validates the proposed method is more effective. In Q5, we can observe that users prefer to visit more places by using the proposed plan than the baseline.

Moreover, In Q3, the evaluation of "total traveling distance" showed that the proposed method can provide a better plan for traveling. However, in Q1 and Q4, there are many comments on the proposed and baseline method as "neither", thus the improvement of guide order should be considered in the next stage of this research.

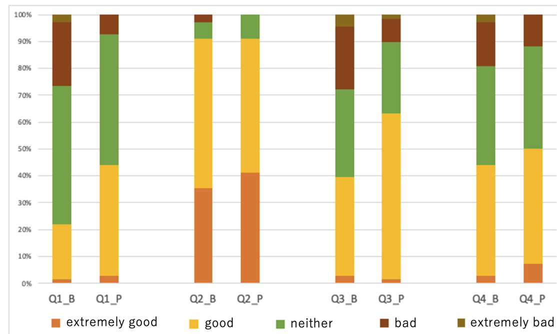


Figure 5. Results of Q1, Q2, Q3 and Q4.

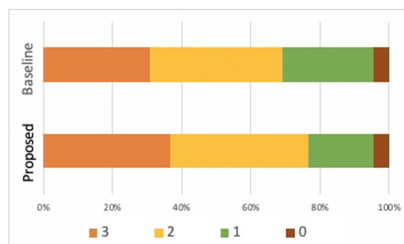


Figure 6. Q5: How many of the recommended POIs would you like to visit?

7. Conclusion

In this study, we proposed a new User-POI-Guide cost optimization method for tourism planning considering the user preferences and concept of “social distance” in response to the situation in the post-COVID-19 era. Our proposed system can recommend the tour guides, scenic spots, and route planning to provide a real-time tour guide plan, which addressed user’s preferences and reduced the face-to-face communication to users in advance. The experiment results showed that based on spatio-temporal constraints of guides to and users, our proposed cost optimization method can also recommend the multiple spots and guides, and supply the suggested route with the minimum cost.

At the current stage, we didn’t use the “age” variable in our system, we plan to consider more variables for cost optimization in the future. We also plan to compare the proposed system with other existing tourism recommendation systems to verify the validity of our proposed method. Moreover, to achieve an even more effective travel guide sharing service, we are going to increase the amount of POI data and real guide data to solve the problem of visibly lower results for the route in our proposed method. Our ultimate goal is to construct a high-quality user-POI-guide cost optimization method for a wider spectrum of tourism guide planning recommendation systems in the post-COVID-19 era.

Acknowledgments

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