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DEVELOPMENT OF A TRAVEL PLANNING SUPPORT SYSTEM USING CONGESTION INFORMATION AND LARGE LANGUAGE MODELS

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Abstract

Tourism destinations in Japan are facing increasingly serious crowding as visitor numbers continue to rise. While congestion-information services have become more widespread, many primarily provide current or predicted congestion levels and offer limited guidance on how tourists should adapt their behavior. In particular, practical support remains insufficient for choosing routes and transportation modes in response to changing crowd conditions. This study develops a congestion-aware sightseeing itinerary planning support system for Kanazawa City that produces personalized travel plans through natural-language interaction and data-driven optimization. The proposed system combines a language-based interaction module with an itinerary optimization module. First, the interaction module interprets a tourist's free-form input and transforms it into a structured set of preferences and constraints, such as available time, starting point, thematic interests, acceptable travel effort, mobility considerations, and attractions that must be visited or avoided. Next, the optimization module generates a feasible itinerary by simultaneously considering predicted crowding at each attraction, travel time and connectivity between attractions for multiple transport options, opening hours, and user-specific requirements. It then selects an itinerary that aims to mitigate exposure to congestion while maintaining feasibility and overall plan quality. The resulting itinerary is presented in natural language, including proposed routes and suggested transport choices, together with concise explanations grounded in congestion and feasibility constraints. By integrating congestion prediction with itinerary optimization and conversational input processing, the proposed approach advances beyond conventional services that merely display congestion levels. The developed framework is intended to provide practical decision support for tourists and may help them adjust sightseeing behavior in line with anticipated crowd dynamics, while maintaining individualized travel experiences and travel convenience.

Keywords: LLMs, congestion information, sightseeing behavior

1 Introduction

International tourism, which declined substantially during the COVID-19 pandemic, has rapidly rebounded. In 2024, the number of international tourist arrivals worldwide reached approximately 1.4 billion, recovering to about 99% of the pre-pandemic level [1]. Tourism is a critical industry accounting for around 10% of global GDP and 10% of total employment [2]. While this recovery is a positive sign, the increase in tourists has also exacerbated overtourism-related problems.

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When visitor numbers exceed the carrying capacity of destinations, negative consequences may occur, including reduced visitor satisfaction and revisit intention, long queues, degraded service quality, and difficulties in safety management. Accordingly, destination managers and related stakeholders increasingly require measures to manage and smooth crowding. One approach to mitigating tourist stress associated with crowding is to provide real-time congestion information. Recent studies suggest that appropriately delivering crowding information can induce behavioral changes among travelers. In an experiment by Chang and Lee [3], travelers who received real-time notifications of destination crowding tended to revise their plans and move toward less crowded places. This crowd-avoidance behavior becomes more pronounced when alternative recommendations are accurate and when travelers have limited time. Nevertheless, current crowding-information services still face notable limitations. For instance, Google's "popular times" feature mainly displays crowding at a single place and does not provide actionable guidance regarding subsequent decisions. To effectively smooth crowding across destinations, it is necessary not only to visualize crowding but also to support flexible plan modification based on that information.

In Japan, inbound tourism has also recovered sharply, and crowding problems have re-emerged. During the 2010s, inbound arrivals increased steadily and reached a record high of 31.88 million in 2019. After a near-collapse in 2020–2021 due to entry restrictions, tourism demand rebounded rapidly following the relaxation of restrictions in autumn 2022. In 2025, inbound arrivals reached a new record of approximately 42.68 million [5]. As a consequence of this V-shaped recovery, crowding at popular destinations has intensified again. According to the latest survey by the Japan Tourism Agency, 13.1% of inbound visitors reported "crowding at tourist sites" as a major difficulty during their trip, making it one of the leading sources of dissatisfaction [6]. Notably, more than 40% of those who experienced crowding cited "insufficient congestion/traffic information" as a cause. This implies that dissatisfaction stems not only from crowding itself but also from the inability to anticipate crowding in advance or respond appropriately in real time. Given the expectation of continued growth in inbound tourism, Japan needs mechanisms that accurately predict and communicate crowding and expand tourists' feasible behavioral options. Based on this background, this study addresses the challenge of "visualizing destination crowding and providing crowd-aware travel planning support." Although numerous ICT-based tourism support systems have been proposed, relatively few integrate crowding information into end-to-end itinerary generation. In practice, many travelers learn about crowding only after arriving on site, resulting in ad hoc and reactive avoidance. Moreover, itinerary planning still imposes a considerable burden on travelers, who must synthesize guidebooks and fragmented online information. Recently, LLMs such as ChatGPT have enabled automatic generation of travel plans reflecting individual preferences; however, generating itineraries that explicitly consider crowding conditions remains insufficient. Therefore, this study aims to develop a system that integrates crowding prediction data with AI capable of capturing individual preferences to produce actionable, crowd-aware itineraries.

2 Methodology and system design

2.1 System overview

The proposed system consists of four stages: (i) input understanding (natural language to structured representation), (ii) crowd level estimation, (iii) mobility computation (walking, taxi, and bus), and (iv) itinerary generation and presentation. The system is implemented in Python and executed in a cloud-based notebook environment, where it reads required data files and runs the itinerary-generation pipeline.

Users provide inputs in either Japanese or English. The input-understanding module extracts key elements, such as departure date/time, starting location, destinations, and group size, and converts them into a predefined JSON format. Next, the crowding-prediction module estimates crowd levels on a 1–5 scale for each destination based on the predicted daily visitor-stay population. The mobility-computation module references travel-time tables for walking and taxi travel as well as a local loop-bus timetable to calculate arrival times for each segment. Finally, the itinerary-generation module constructs feasible itineraries by jointly considering crowd avoidance and total travel time, and the output-formatting module presents the results in both Japanese and English.

For input understanding, we employ an LLM to extract itinerary-relevant elements from user utterances. Specifically, we use gpt-4o-mini via the OpenAI API. Because natural language inputs can be ambiguous, we prioritize minimizing missing elements required for computation and normalizing extracted values into a granularity suitable for constraint handling. For itinerary generation, the system integrates structured inputs with predicted crowd levels, travel times, and bus schedules to produce time-ordered, feasible itineraries. For each segment, the system outputs departure time, arrival time, transportation mode, travel duration, predicted crowd level at the arrival time (with a brief explanation), and recommended stay duration. The system also reports total travel time and total cost for the entire itinerary. To support decision-making, two alternative itineraries with different transportation strategies are presented so that users can understand trade-offs between time and cost. When the estimated crowd level exceeds a threshold, the system additionally provides a taxi-based alternative as a time-saving option and explicitly reports the associated increase in cost.

2.2 Data used in the system

Crowd level estimation is conducted using destination-specific daily time-series data of crowding indicators, for which we apply a SARIMAX model for each attraction. The crowding indicators are constructed based on KDDI Location Analyzer data [7]. During model training and evaluation, periods with substantial structural changes in tourism demand, such as pandemic-affected intervals, are excluded in order to primarily capture regular cyclical patterns under normal conditions. Since itinerary generation requires crowding information that can be used in the itinerary context, the predicted daily visitor-stay population is classified into five crowding levels using predefined thresholds. These five-level indicators are then used as crowding information for itinerary generation. The travel times for walking and taxi are compiled into pairwise travel-time tables using Google Maps as a consistent reference source. For bus travel, we utilize the timetable of the Jokamachi Kanazawa Loop Bus provided by Hokuriku Railroad and compute arrival times by searching for the next available departure after the current time [8].

Table 1 Sample of data used for developing the crowding prediction model

Year	Month	Day	Kenrokuen	Higashi	Omicho	Station	Museum	Nagamachi	Rain	Snow	Holiday
2018	1	1	11,329	7,086	1,777	17,100	333	694	8	0	1
2018	1	2	8,350	3,247	3,970	27,768	3,215	667	10	1	0
2018	1	3	6,675	5,628	4,884	23,262	3,155	237	22	7	0
2018	1	4	5,098	3,933	4,124	16,084	3,240	427	19.5	10	0
2018	1	5	4,387	2,972	7,572	14,570	3,769	309	0	0	0
2018	1	6	5,123	6,040	10,001	18,954	3,333	1,539	3	0	0
2018	1	7	7,286	4,400	7,564	17,907	3,365	1,264	0	0	0
2018	1	8	8,464	3,041	6,230	15,541	2,086	483	12.5	0	1
2018	1	9	1,450	1,918	5,491	7,387	950	1,126	17.5	0	0
2018	1	10	1,893	1,981	4,789	9,876	1,671	2,012	31	4	0

2.3 Overview of the prediction model

In this study, a crowding prediction model was developed for major tourist attractions in Kanazawa City. The target locations were six major sightseeing spots: Kenrokuen Garden, Higashi Chaya District, Omicho Market, the east exit area of Kanazawa Station, the 21st Century Museum of Contemporary Art, Kanazawa, and the Nagamachi Samurai District. In addition to daily visitor-stay data obtained from KDDI Location Analyzer, supplementary explanatory variables were used, including weather-related factors, holiday-related factors, and facility-related factors. For the data split, 1,758 days from January 1, 2018 to October 7, 2024, excluding the period affected by COVID-19, were used as the training period. The subsequent 439 days, from October 8, 2024 to December 20, 2025, were used as the test period. For daily prediction, this study adopted a SARIMAX model, which can account for both seasonality and exogenous variables. The model specification was set as order = (1,1,1) for the non-seasonal component and seasonal_order = (1,1,0,7) for the seasonal component, thereby incorporating weekly periodicity. As common exogenous variables across all locations, day-of-week dummy variables, rain, snow, holiday, weekend, and temp_avg were included. In addition, to reflect location-specific factors, omicho_closed was added for Omicho Market; museum_closed, museum_temp_closed, and museum_partial_closed were added for the museum; and kenrokuen_event was added for Kenrokuen Garden. After model training, daily visitor-stay numbers during the test period were predicted, and the results are shown in figure 1.

Prediction accuracy was evaluated using MAE, RMSE, and MAPE. The MAPE values were 15.35% for the east exit area of Kanazawa Station, 25.53% for Omicho Market, 30.02% for Higashi Chaya District, 41.09% for the Nagamachi Samurai District, 44.66% for the 21st Century Museum of Contemporary Art, Kanazawa, and 53.67% for Kenrokuen Garden. These results indicate that relatively high prediction accuracy was achieved for the east exit area of Kanazawa Station, which functions as a major transportation hub and exhibits relatively stable usage patterns. In contrast, relatively large prediction errors remained for locations such as Kenrokuen Garden and the 21^{st} Century Museum of Contemporary Art, Kanazawa, where visitor numbers are more strongly affected by seasonal events, tourism peaks, exhibition contents, and temporary closures.

Furthermore, rather than presenting the predicted daily visitor-stay numbers directly, this study converted them into five-level crowding indicators so that tourists and administrative stakeholders could understand the results intuitively.

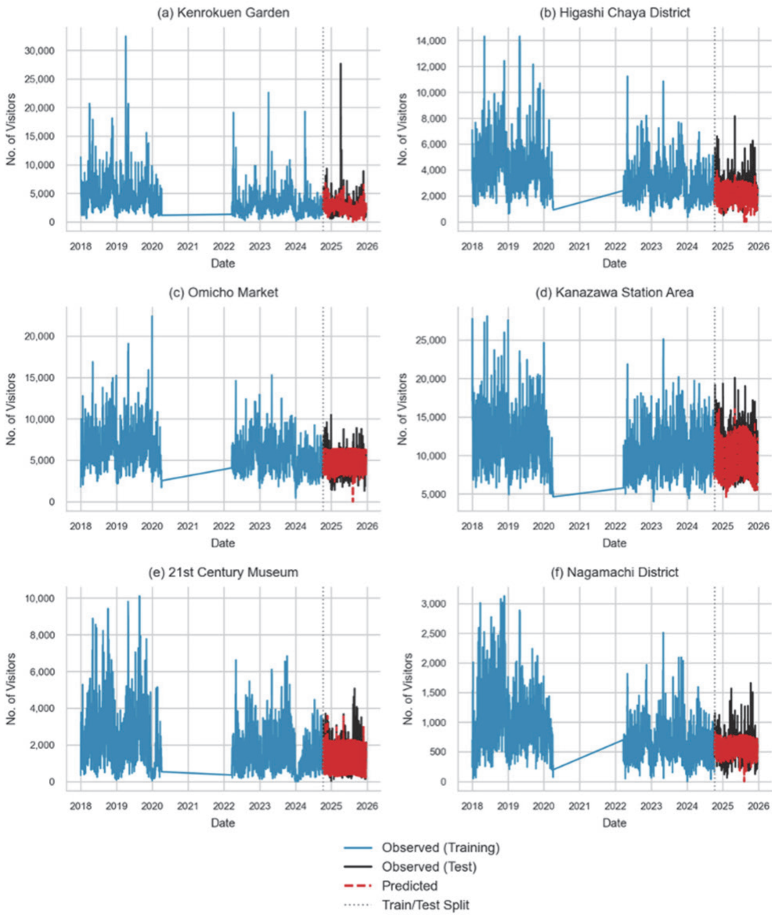

Figure 1 SARIMAX forecast results

2.4 Example output

Figure 2 illustrates an example output. In this experiment, we input: "Depart from Kanazawa Station at 10:00, visit Kenrokuen Garden, and then go to the Nagamachi Samurai District". The system extracts the starting location, two destinations, and departure time, structures them into the computation-ready format, and then generates itineraries based on crowding predictions and mobility calculations. Because the output provides a chronological sequence of times and transportation modes, users can understand, in an integrated manner, "when to go where, by which mode, how long it will take, and how crowded it is expected to be". Moreover, the total travel time and total cost enable users to compare alternative itineraries.

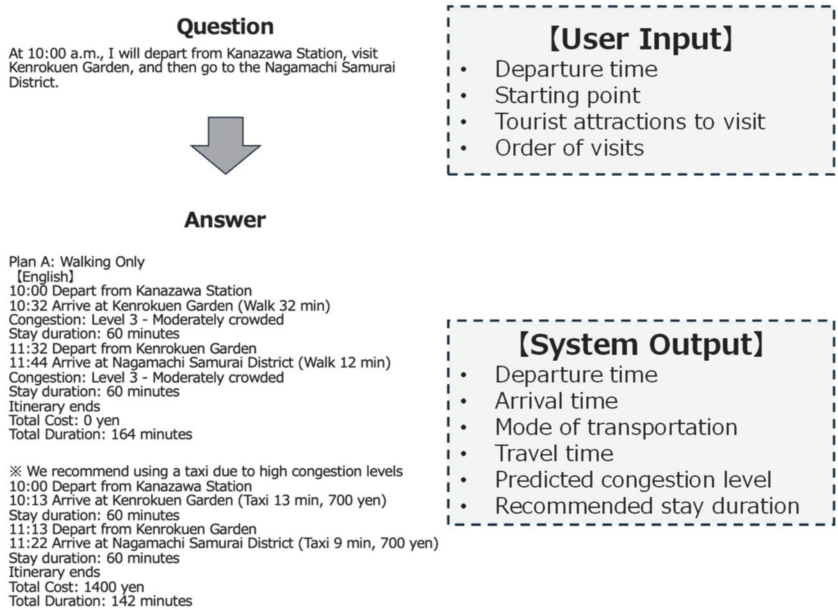

Figure 2 Example of a response generated by the developed system

2.5 Discussion on output usefulness

Because this study focuses on developing an end-to-end itinerary-generation pipeline, we qualitatively demonstrate how the output can be used as decision support using the same input scenario shown in figure 2. In the output, each destination is accompanied by a crowd level aligned with the expected visiting time, along with a short explanatory text. This presentation allows users to interpret expected crowding in the context of their planned sequence without separately consulting crowding maps or other services, thereby reducing the cognitive effort required to translate congestion information into concrete actions. In addition, when the predicted crowd level exceeds a specified threshold, the system appends a taxi-based alternative itinerary as a time-saving option and reports both reduced travel time and increased cost. For example, in the demonstrated scenario, the taxi alternative is shown together with the estimated additional cost and the corresponding reduction in total duration, making the time–cost trade-off explicit relative to walking-only or bus-based plans. Such structured alternatives are expected to help users compare feasible options under crowded conditions, even when they prioritize different objectives (e.g., minimizing cost versus reducing travel burden and time).

3 Conclusion

This study developed a decision-support system for Kanazawa City that goes beyond merely visualizing crowding by integrating crowding prediction with mobility and stay-time constraints for itinerary generation. The developed system uses an LLM to structure user inputs and combines SARIMAX-based crowding prediction with travel-time tables (walking and taxi) and bus timetable-based computations to generate feasible itineraries. By presenting two alternative plans, the system improves comparability and supports decision-making.

By embedding crowding information into the itinerary context, users can reduce the additional cognitive burden of interpreting crowding data and translating it into concrete actions. Presenting two alternatives in a consistent format also enables users to choose plans based on preferences such as minimizing cost versus reducing travel burden and time. Nevertheless, the system has limitations. Prediction errors may increase under exogenous factors such as events or sudden weather changes, and real-time operational information (e.g., bus delays) is not yet incorporated.

References

[1] World Tourism Barometer: January 2025, UN Tourism, https://en.unwto-ap.org/news/worldtourism-barometer_jan2025/

[2] Tourism Economic Impact Research (EIR), https://wttc.org/research/economic-impact

[3] Chang, J.H., Lee, C.H.: The effect of real-time crowding information on tourists' procrastination of planned travel schedule, Journal of Hospitality and Tourism Management, 56 (2023), pp. 18-28

[4] UN Tourism, A Real-time Safety and Congestion Level Analysis System for Jeju Tourist Sites, https://www.untourism.int/asia/a-real-time-safety-and-congestion-level-analysis-system-for-jeju-tourist-sites

[5] Japan National Tourism Organization, https://www.jnto.go.jp

[6] Japan Tourism Agency, https://www.mlit.go.jp/kankocho/content/001882886.pdf

[7] KDDI Location Analyzer, https://k-locationanalyzer.com

[8] Kanazawa Loop Bus, https://www.hokutetsu.co.jp/tourism-bus/castle-town/