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Adaptive Travel Solutions: The Role of ChatGPT in Dynamic Itinerary Generation

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Abstract. This study discusses the integration of ChatGPT into a personalized travel advisor platform. Currently, travelers face an overwhelming amount of information when planning their trips, which can diminish the enjoyment and effectiveness of travel preparation. To address this issue, we designed an AI-powered travel advisor that generates tailored itineraries based on user inputs, such as destination, budget, and preferences. The development process included user research, low-fidelity prototyping, and usability testing. In this paper, we explore whether incorporating AI into travel planning can enhance user experience and improve the efficiency of trip preparation. With the real-time responses generated by ChatGPT, users can receive more dynamic, relevant, and personalized travel plans compared to traditional search engines. This approach not only simplifies the travel planning process but also provides a more engaging and intuitive user experience.

Keywords: AI-Travel Interaction, Web design, Personalized travel planning, ChatGPT.

1. Introduction

1.1. Background Intro

The integration of AI in the travel industry has rapidly transformed the landscape, offering a more efficient, personalized, and cost-effective experience for both travelers and companies. AI-powered chatbots are now capable of handling up to 80% of customer queries, significantly reducing response times and improving customer satisfaction. Additionally, AI has optimized pricing strategies and operational efficiencies, helping companies save up to 70% on service costs. The technology also enhances fraud detection, increases booking conversion rates by up to 70%, and supports dynamic pricing, which further boosts revenue. AI's ability to personalize marketing campaigns and recommendations, improve search accuracy, and streamline airport operations is reshaping how we explore the world. With projections indicating that AI will manage up to 90% of customer interactions

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by 2025, the future of travel is increasingly dependent on smart technology, paving the way for seamless, tailored experiences for travelers globally.[1]

1.2. Application Intro

The emergence of artificial intelligence products like ChatGPT has led the travel industry to start embracing AI to improve and personalize trip planning. Currently, travelers have to sift through an overwhelming amount of information when planning their trips, making the process consume lots of time and be less enjoyable. Traditional methods of traveling often involve much manual research between multiple platforms, which may lead to overlooking opportunities for tailor-made experiences. AI can address these pain points by analyzing user preferences, budgets, and travel goals to generate personalized itinerary recommendations.

With ChatGPT, the travel platforms make real-time, personalized recommendations that improve the user experience and engagement. Most travelers are looking for unique experiences, and AI will help optimize the entire journey, from destination and activity suggestions to cost management and accommodations.[2] Despite the growing presence of AI in the travel industry, there are still gaps in developing integrated, user-centered tools that put all aspects of travel planning into one seamless platform. Therefore, this research attempts to address these challenges by conceptualizing an AI-powered travel advisory system utilizing ChatGPT's API to enhance the process and improve both the user experience and efficiency in travel planning.

2. Initial Design

We designed a travel advisor that combines ChatGPT with an attractive user interface to create a more personalized travel planning experience. The app's main function is to provide customized travel itineraries based on user inputs about destinations, budgets, interests, and travel time. It allows users to input their preferences using a simple interface and results in real-time recommendations from AI.

The most important design concept is a user-friendly, step-by-step interface: a user could answer questions about their trip, e.g., where they are going, whether they have any place in mind, or want recommendations based on previous experiences. The AI will then use the data provided by the user to generate an itinerary that includes recommended activities, accommodation choices, modes of transportation, and restaurants. In addition, users can update the information in real time to alter their preferences, and the AI will adjust the plan accordingly. For users who would want more direct customization, it features a ChatGPT-driven chatbot that answers specific travel-related questions, among other things, for advice and alternatives. Essentially, this is designed to overcome potential problems in travel planning, such as information overload on the user interface, by offering a page that responds to more advanced questions. The application also uses Google Maps for location-based suggestions and navigation, enabling users to plan appropriately based on traffic information.

This AI-powered travel assistant is proposed to further improve user efficiency in tour planning by providing tailored suggestions that match user preferences. At the same time, it will reduce the stress and complexity traditionally associated with travel planning and using AI products.

3. Iteration #1: Need Recognizing

3.1. Need Finding

During its initial development phase, the focus lay primarily on recognizing potential users' needs and pain points in the travel planning process. Exploratory research shows that modern-day travelers have a number of significant challenges to grapple with: information overload coming from numerous platforms, difficulty with personalization of experiences, too much time consumption, and frustration with budget constraint management, among others. What most users want, therefore, is a more streamlined, easy tool to help avoid such issues. A study[3] of the current travel planning tool ecosystem pointed toward the high adoption of online travel agencies and various recommendation systems. In addition, only a few solutions offer personalized end-to-end solutions that take into consideration the

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real-time preferences of travelers. While a few AI-powered travel chatbots exist, most of them can only provide basic short itineraries that cannot be practically applied. These findings indicated a significant gap in the market for a more advanced AI-powered travel planner.

3.2. Survey Objective

The primary goal of our survey was to identify the key pain points, preferences, and behaviors of potential users of our travel advisor app. We want to gather opinions from a diverse group of individuals, focusing on people who travel frequently and occasional vacationers, to inform the design and functionality of the app.

3.3. Survey Design

The survey contains multiple-choice, Likert scale rating questions and several open-ended response questions. It covered the following key areas: pain points encountered during travel planning, preferences for AI-powered tools and desired features, and comfort level with using AI models for tasks like itinerary generation.

3.4. Sample Collection

In order to get a more representative and broader sample, we conducted our survey on the University of Washington campus. We ran a survey among teachers, staff, and students who had either traveled recently or intended to do this in the future. The diverse student body of the university, which included both domestic and foreign students, offered a rich sample for analyzing various travel habits.

The questionnaire was purposefully created to be accessible in print and digital formats:

Physical distribution: We set up our survey booths at high-peaking student flow areas, such the student center and university library, during peak times.

Digital distribution: On-campus sampling has also been done, and options such as university mailing lists or other means, e.g., travel enthusiasts' groups on Facebook, could be used since we wanted more respondents who may not visit actual campus locations. By using this method, we were able to capture a wide range of participants.

We are mainly concentrating on frequent travelers, backpackers, and leisure vacationers. To ensure the sample would be relevant, all surveys started with a filter question: "Have you traveled within the past year, or are you planning a trip in the next six months?" The full survey was administered to only those who had responded "Yes" to this question.

We got a total of 150 contributions from users spanning multiple different age groups (18–50+), travel experience levels, and purpose of the trip. Our sample is divided as such:

- Undergraduate students (40%)
- Graduate students (35%)
- Faculties and staffs members (25%)

The demographics spanned those who travel on a regular basis (25%), those who only take holidays now and again at best (50%), and business travelers working across all sectors of industry for their organizations (15%).

3.5. Key Survey Results

Participants were asked about their biggest challenges when planning trips. They could select multiple options; the results are shown in Table 1.

Table 1. Pain Points in Travel Planning

Pain Points	**Percentage of Respondents (%)**
Information Overload	70%
Time Constraints	60%

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Table 1. (continued).

Budget Management	55%
Lack of Personalization	65%
Difficulty in Finding Reliable Information	50%

Specific Data Points:

- **105 participants (70%)** indicated they were overwhelmed by online information. Many also mentioned that they had to turn to several sites to compare prices and read reviews, which undoubtedly took longer.
- **90 participants (60%)** stated that they struggled with time scheduling, often finding it hard to allocate sufficient time for detailed trip planning.
- **83 participants (55%)** indicated difficulties handling the travel budget. This suggests they were struggling to balance cost savings against experience preservation.

Participants were asked to select features that would be most useful in the travel advisor. They could select multiple options; the results are shown in Table 2.

Table 2. Desired Features in the AI-Powered Travel Advisor

Desired Features	**Percentage of Respondents (%)**
Personalized Itineraries	65%
Accommodation Suggestions	80%
Activity Recommendations	75%
Budget Optimization	60%
Real-Time Adjustments	55%

Specific Data Points:

- **120 participants (80%)** emphasized the need for accurate and convenient accommodation suggestions, based on their budget and preferences.
- **113 participants (75%)** were most interested in receiving activity recommendations specific to their interests such as cultural experiences, adventure or local dining options.
- **98 participants (65%)** wanted very specific personalized itineraries that best met their travel aims and desires; including duration, budget parameters and interests.

Participants scored how comfortable they were using AI-powered travel planning tools. As can be seen from the breakdown in Table 3, most respondents were open to integrating AI into their travel experience.

Table 3. Comfort Level with AI Tools

Comfort Level with AI Tools	**Percentage of Respondents (%)**
Very Comfortable	30%
Somewhat Comfortable	45%
Neutral	15%
Somewhat Uncomfortable	7%
Very Uncomfortable	3%

Specific Data Points:

- **45 participants (30%)** reported being “very comfortable” with AI-powered travel tools, showing enthusiasm for AI-driven recommendations of trip planning.

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- **68 participants (45%)** said they were “somewhat comfortable,” indicating a general willingness to try AI-powered features, though they still valued having manual control over certain aspects of their travel plans.
- **11 participants (7%)** felt “somewhat uncomfortable” with AI handling their travel plans, citing concerns about accuracy and lack of human touch.

3.6. Summary of Findings

The results from our survey show that there is a demand for an AI-powered travel advisor that solves the three primary issues that travelers face when planning a trip: time constraints, personalization, and information overload. When using artificial intelligence to provide recommendations for activities, accommodation, and itineraries, most participants reported a high degree of comfort. Customized itineraries, budget optimization, and real-time adjustments were the most requested features by consumers, indicating that they are looking for a more customized experience that can be arranged more quickly and with more flexibility.

4. Iteration #2: Design Low-fi Prototype

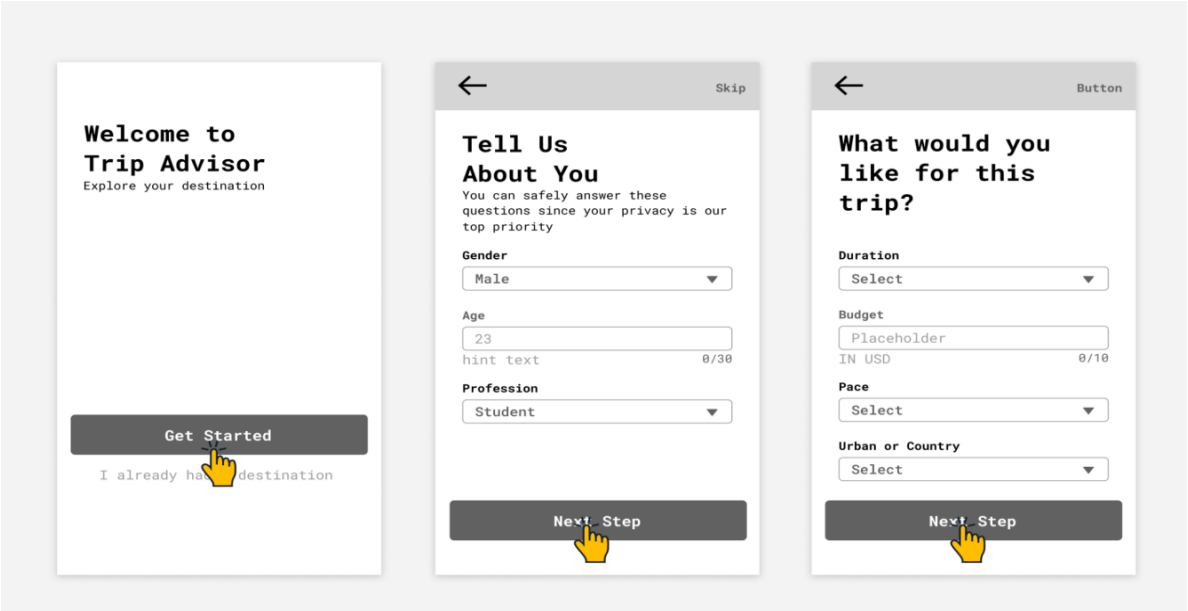


Figure 1. Screenshots of The Homepage And Customization Page

The low-fidelity prototype design of the AI Travel Advisor begins with the homepage, where users are provided with two options: whether they have chosen a location or they are still looking into ideas. Users can select the other option if they want to, but the UI defaults to assuming they didn't decide on a destination. Users are directed to a customisation page by a large "Next Step" button once they have made their choice. On this page, In order to customize the travel experience, users have to answer an array of background questions on this page. Basic demographics like age and gender are covered, as well as specific travel preferences like spending cap, length of trip, and preferred arrival and departure dates. Users are also asked about whether they prefer to travel in urban or rural environments, along with about how quickly or slowly they prefer to travel.[4] The system inquires about their journey companions in order to further personalize recommendations, offering options such as parents, partners, friends, or other individuals.

```
const conversationHistory = [
{
  role: 'system',
```

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```
      content: 'You are a trip advisor and planner. You help users plan trips by providing
recommendations for food, lodging, natural experiences, and cultural experiences.'
    },
    {
      role: 'user',
      content: `Please Generate a Travel Guidance in ${impressiveLocation}from 5 perspectives:
dining, residence, transportation, natural view, and cultural landscape`
    }
];
```

In this preprocessing step for the conversational model, I have designed a structured input sequence to optimize the interaction between the user and the AI for generating personalized travel recommendations. The conversation history begins by establishing the system's role as a "trip advisor and planner," which clearly defines the model's function as providing travel guidance based on various key categories. By setting this context in the system's role, the model is primed to understand that its responses should be focused on offering specific, actionable recommendations related to food, lodging, natural experiences, and cultural experiences.[5] This ensures that the model remains within the domain of travel planning and delivers output that aligns with user expectations.

Following this, the user's input is carefully structured to include the destination they are interested in, with an explicit request for travel guidance from five different perspectives: dining, residence, transportation, natural views, and cultural landscapes. By breaking the request down into these distinct categories, I ensure that the model's output will comprehensively cover various aspects of the travel experience, thus providing a more complete and well-rounded recommendation. This methodical approach to framing the conversation helps guide the AI's response generation, allowing it to focus on the most relevant aspects of the user's inquiry and produce a detailed, tailored travel plan. Through this preprocessing strategy[6], I aim to enhance the coherence and relevance of the model's output, making it more aligned with the user's specific needs and preferences.

5. Participatory Design I

After completing the low-fidelity prototype of the AI-powered travel advisor, I conducted participatory design sessions by reaching out to the interviewees from our earlier surveys through the campus WeChat group. The goal was to gather their impressions, suggestions, and any concerns they might have about the prototype. These participants, who represented a diverse group of travelers, were very interested in the personalized travel planning features of the model. However, they raised an important issue regarding transparency in the AI's recommendations, particularly in terms of understanding the source of the data used by ChatGPT to generate travel suggestions.

5.1. Key Feedback from Participants:

The primary concern expressed by users was the **lack of transparency** in the AI's recommendation process. Users felt that while the AI provided personalized destination suggestions, it did not communicate the rationale behind these recommendations or the specific datasets it used. One participant remarked, "I don't know how the AI decides which places are the best for me—it doesn't explain where it's getting the data from, and that makes me hesitant to fully trust the recommendations." This feedback highlighted a critical gap in user trust and the need for clarity in the decision-making process of the AI system.

Participants expressed that knowing the source of information—such as whether the AI was basing its recommendations on widely available travel reviews, user-generated content, or professional opinions—was crucial for them to fully engage with and trust the platform. They wanted insight into how the system arrived at certain destination choices, such as why a particular restaurant or activity was suggested over others.

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5.2. Response to User Feedback:

In response to this feedback, we began exploring ways to improve the transparency of the recommendation process within the AI travel advisor. To address the users' concerns, we developed a strategy for enhancing the explainability of the AI's destination suggestions by integrating external data sources that users are familiar with and trust. Specifically, we decided to **leverage reviews and comments from two major platforms**: Google Maps and Xiaohongshu (China's largest photo-sharing and review platform).

5.3. Solution: Crawling Data from Google Maps and Xiaohongshu

The idea we formulated involved **crawling user-generated reviews and comments** from Google Maps and Xiaohongshu to create a more robust and explainable dataset for the AI. By extracting key insights and keywords from reviews—such as mentions of specific attractions, dining experiences, transportation details, and cultural highlights—we could categorize each destination based on real traveler experiences. This method would allow the AI to generate recommendations that are not only personalized but also grounded in reliable, user-provided feedback.

For instance, when the AI suggests a restaurant or a natural landmark, it would be able to explain its recommendation by citing frequent positive comments from Google Maps reviews (e.g., "This restaurant is highly rated for its unique local cuisine and friendly service") or pulling data from Xiaohongshu posts that highlight popular activities or lesser-known attractions (e.g., "Travelers on Xiaohongshu often mention this location for its serene hiking trails and scenic views"). This would give users more confidence in the AI's recommendations and provide transparency into the decision-making process.

5.4. Enhanced Trust and User Experience:

This approach addresses the participants' desire for more clarity and trust in the AI system. By incorporating reviews and insights from established platforms like Google Maps and Xiaohongshu, the AI-powered travel advisor can now explain its recommendations in a way that resonates with users. Additionally, these platforms offer diverse perspectives, allowing the AI to provide more varied and well-rounded suggestions that cater to different travel styles and preferences.

To ensure the integration of this data remains efficient and user-friendly, we designed the system to display a brief explanation of each recommendation, along with a citation of the source (e.g., "Based on 500+ reviews from Google Maps" or "Popular destination on Xiaohongshu"). This not only enhances transparency but also enriches the user experience by linking recommendations directly to real-world feedback.

6. Design High-Fi Prototype

6.1. Adaptive Algorithm Tuning for Destination Recommendations

A critical component of creating an effective AI-powered travel advisor is fine-tuning the underlying recommendation algorithm to ensure it captures the nuances of user preferences. For this purpose, we implemented an adaptive algorithm, where user choices progressively refine the model's suggestions, allowing it to dynamically adjust to individual travel styles.

Preprocessing and Structured Input

In order to ensure the model accurately captures user preferences, we designed a multi-step input process where user responses are segmented into key categories (e.g., "food," "lodging," "natural experiences," and "cultural experiences"). This structured format ensures that the model understands the distinct elements of a travel plan and aligns them with relevant destination features.

We tailored the model to parse user inputs using keywords that correspond to these categories, allowing it to filter out irrelevant information. By instructing the model to prioritize certain attributes, we ensure that the AI delivers destination recommendations that are highly relevant to user-defined

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needs. For instance, a user may express interest in cultural experiences in urban settings, while another may prioritize natural environments for relaxation.

```
const userPreferences = {
  food: "local cuisine",
  lodging: "budget hotels",
  natural_experiences: "hiking trails",
  cultural_experiences: "museums"
};

const destinationData = [
  {
    name: "Kyoto",
    food: ["kaiseki dining", "local cuisine"],
    lodging: ["traditional ryokan", "budget hotels"],
    natural_experiences: ["bamboo forests", "hiking trails"],
    cultural_experiences: ["temples", "museums"]
  },
  {
    name: "New York",
    food: ["street food", "fine dining"],
    lodging: ["luxury hotels", "budget hotels"],
    natural_experiences: ["parks", "urban walking tours"],
    cultural_experiences: ["galleries", "museums"]
  }
];

function recommendDestination(preferences) {
  return destinationData.filter(destination => {
    return Object.keys(preferences).every(key =>
      destination[key].includes(preferences[key])
    );
  });
}

const recommendations = recommendDestination(userPreferences);
console.log("Recommended destinations:", recommendations);
```

This structured approach allows the algorithm to make more precise recommendations based on user input, filtering out irrelevant destinations and focusing on those that match the user's preferences. The above code snippet shows how we dynamically adjust destination recommendations based on real-time user input, ensuring the recommendations align with the user's specific preferences across multiple categories.

6.2. Integrating Real-Time Data from External Source

To enhance the relevance and trustworthiness of our destination recommendations, we integrated real-time data from trusted external sources like Google Maps and Xiaohongshu. This addition addresses user feedback regarding the need for transparency and reliability in AI-driven recommendations, allowing the system to offer insights grounded in real user experiences.

Crawling Reviews from Google Maps and Xiaohongshu

By extracting relevant keywords and user-generated content from these platforms, we ensured that the AI was making recommendations based on accurate, up-to-date feedback from other travelers. The

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system crawls user reviews and ratings to gather detailed insights into specific aspects of each destination, such as food quality, natural landscapes, and cultural experiences.

```
const fetchReviews = async (location) => {
  const googleMapsApiUrl = `https://maps.googleapis.com/maps/api/place/details/json?*******=${location.place_id}&key=*********`;

  const response = await fetch(googleMapsApiUrl);
  const data = await response.json();

  const reviews = data.result.reviews.map(review => ({
    rating: review.rating,
    text: review.text
  }));

  return reviews;
};

const kyotoReviews = await fetchReviews({ place_id: 'ChIJyWEHuEmuEmsRm9hTkapTCrk' });
console.log("Kyoto reviews:", kyotoReviews);
```

By integrating external data, we can now provide transparent and trustworthy travel suggestions. For example, when recommending a restaurant, the model can cite real-world reviews from platforms like Google Maps, offering a more reliable basis for its recommendations. This significantly enhances the model's credibility and improves the user's confidence in the system's suggestions.

6.3. Adaptive Keyword Matching for Personalized Travel Plans

As part of our algorithm tuning, we employed keyword matching to ensure that the model extracts the most relevant information from user inputs. This step involves mapping user preferences to destination attributes using a predefined set of keywords, ensuring a high degree of personalization in the travel recommendations.

Keyword Matching Algorithm

We designed a simple keyword matching algorithm that compares user input (e.g., "I love hiking and local food") with predefined tags in our destination dataset. The model then ranks the destinations based on how closely they align with the user's expressed preferences.

```
const keywords = {
  food: ["local food", "fine dining", "street food"],
  natural_experiences: ["hiking", "beach", "forests"],
  cultural_experiences: ["museums", "galleries", "temples"]
};

function matchPreferences(userInput, destination) {
  let score = 0;
  Object.keys(keywords).forEach(category => {
    keywords[category].forEach(keyword => {
      if (userInput.includes(keyword) && destination[category].includes(keyword)) {
        score++;
      }
    });
  });
  return score;
```

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```
}

const userInput = "I love hiking and local food";
const bestMatch = destinationData.map(destination => ({
  name: destination.name,
  score: matchPreferences(userInput, destination)
})).sort((a, b) => b.score - a.score);

console.log("Best matching destination:", bestMatch[0].name);
```

This keyword matching approach helps the model efficiently capture user intent and ensure that the recommendations align with their specific interests. By focusing on keyword extraction, we ensure that the algorithm delivers highly relevant results based on user input, offering a more personalized travel plan.

6.4. Enhancing Transparency and Explainability in AI Recommendations

Another critical aspect of building trust in AI-powered systems is providing transparency in how recommendations are made. To address the transparency concerns raised by participants in the participatory design phase, we implemented an explanation system that provides users with a rationale for each recommendation.

Explainability Integration

The AI system now generates explanations alongside its recommendations, detailing how it arrived at a particular suggestion. For instance, when recommending a specific destination, the model explains its decision by referencing key attributes such as highly rated restaurants or popular natural landmarks, sourced from real user reviews or data crawled from external platforms.

```
function generateExplanation(destination, userPreferences) {
  const reasons = [];

  if (destination.food.includes(userPreferences.food)) {
    reasons.push(`The food scene in ${destination.name} matches your preference for ${userPreferences.food}.`);
  }
  if (destination.natural_experiences.includes(userPreferences.natural_experiences)) {
    reasons.push(`${destination.name} offers excellent ${userPreferences.natural_experiences} opportunities.`);
  }

  return reasons.join(" ");
}

const explanation = generateExplanation(recommendations[0], userPreferences);
console.log("Recommendation explanation:", explanation);
```

By offering users insight into why specific recommendations were made, the system builds trust and fosters user engagement. This transparency feature not only enhances the user experience but also addresses the concerns raised during the participatory design phase.

7. Participatory Design

The next phase of the project involved conducting participatory design to evaluate the AI-powered travel advisor's ability to recommend destinations that align with user preferences. The primary goal of this phase was to test whether the model's predictions matched user expectations, and to gather insights for further refinement. This process involved designing a survey to capture user feedback, analyzing the collected data, and comparing the performance of two different versions of the model.

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We began by designing a detailed survey aimed at evaluating the model's recommendation accuracy and user satisfaction. The survey was divided into three sections. In the first section, participants were asked a series of structured questions about their travel preferences, such as the type of experience they sought (e.g., cultural, natural, adventure, urban), preferred climate (e.g., warm, cold, temperate), and travel companions (e.g., solo, family, friends). These questions were designed to gather data that the model could use to generate destination recommendations. The second section allowed participants to provide freeform input, describing their ideal vacation in their own words. This part of the survey aimed to test how well the model could interpret open-ended user input and generate relevant recommendations. In the third section, participants evaluated the recommended destinations they received from the model. They rated the accuracy of the match (1 to 5), their overall satisfaction (1 to 5), and the diversity of the recommended destinations (1 to 5). In addition, they provided qualitative feedback on the model's performance, offering insights into whether the recommendations aligned with their travel expectations.

We conducted the survey with 50 participants, ensuring a diverse sample that included frequent travelers, occasional vacationers, and individuals planning upcoming trips. Participants completed the survey after interacting with the travel advisor system, and their responses were used to evaluate two different model configurations: Model A, which used basic keyword matching to recommend destinations, and Model B, an enhanced adaptive model that incorporated real-time data from external sources and used more sophisticated keyword matching algorithms.

The results from the survey highlighted clear differences in performance between the two models. As shown in Table 4, Model B significantly outperformed Model A in key areas such as matching accuracy, user satisfaction, and the diversity of recommendations. When participants rated the accuracy of the model's recommendations on a scale of 1 to 5, Model A received an average score of 3.2, while Model B scored 4.6. Similarly, user satisfaction with Model B was notably higher, with an average score of 4.4 compared to 3.1 for Model A. Participants also rated the diversity of recommendations more favorably for Model B (4.5) than for Model A (2.9), indicating that the enhanced model provided a broader range of destination options, whereas Model A tended to deliver repetitive results. The percentage of participants who felt that the recommended destinations aligned with their ideal vacation increased from 62% with Model A to 88% with Model B.

Table 4. The Result of Performance for Model A and B

Metric	**Model A (Basic Keyword Matching)**	**Model B (Enhanced Adaptive Matching)**
Matching Accuracy (1-5 scale)	3.2	4.6
Satisfaction (1-5 scale)	3.1	4.4
Diversity of Recommendations (1-5)	2.9	4.5
Participant Agreement (%)	62%	88%

The qualitative feedback further reinforced these quantitative findings. Participants expressed that Model B provided more personalized and varied recommendations, making the travel suggestions feel more tailored to their specific preferences. They noted that the model's ability to incorporate real-time data from external sources, such as user reviews from platforms like Google Maps and Xiaohongshu, added credibility to the recommendations. Several participants highlighted that they trusted the recommendations from Model B more because the system provided explanations for why certain destinations were suggested. For instance, when the model recommended a restaurant or a cultural landmark, it cited reviews or other real-time data, making users feel more confident in the suggestions. In contrast, participants using Model A often reported that the recommendations felt generic and less aligned with their expectations.

The comparison of these two models revealed critical insights into how personalized travel recommendation systems can be improved. Model A, which relied on basic keyword matching, struggled to capture the nuances of user preferences, particularly when dealing with open-ended input.

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In contrast, Model B's adaptive keyword matching and integration of external data allowed it to generate more relevant and diverse recommendations. This model's ability to provide transparent explanations for its recommendations significantly enhanced user trust and satisfaction.

8. Conclusion

In conclusion, the participatory design phase demonstrated that incorporating more sophisticated algorithms and real-time data sources into the travel advisor system substantially improved its ability to deliver personalized and accurate recommendations. Model B's higher performance across all metrics suggests that using adaptive models that can interpret nuanced user inputs and rely on real-world data leads to a more satisfying user experience. The results from this phase will inform further iterations of the system, with the goal of continuing to refine the recommendation process and improving transparency in the AI's decision-making. As the system evolves, future improvements may focus on expanding the dataset, refining the explanation mechanism, and increasing the flexibility of the input options to further enhance the personalized travel experience.

Acknowledgement

We would like to express our sincere gratitude to **Junru Wang**, the first author, whose leadership and expertise were crucial in the success of this project. Junru was the primary force behind the research, taking on a leading role in model training and backend development. Junru not only designed and refined the high-fidelity prototype but also implemented the core functionality of the adaptive algorithm, which enabled personalized and dynamic travel recommendations. Their work on model training was essential in ensuring that the AI could accurately interpret user preferences and generate relevant travel plans. Additionally, Junru played a key role in integrating real-time data sources and managing API connections, which greatly enhanced the model's responsiveness and reliability. Junru was also responsible for conducting user surveys, analyzing feedback, and writing the majority of this paper, demonstrating their comprehensive involvement in both the technical and research aspects of the project.

Special thanks to **Yange Lin**, for contributing to the development of the backend for the low-fidelity prototypes. Yange focused on the implementation of API logic and data handling processes, ensuring smooth interactions between the user interface and backend systems. Yange also provided valuable input during the refinement of the model's architecture and assisted in drafting sections of the paper related to system infrastructure and technical development.

We would also like to acknowledge **Tianxin Chen**, the contributing author, for their efforts in auditing and validating the collected data. Tianxin played an important role in reviewing user feedback and ensuring the accuracy of the survey data, which was critical to the iterative improvement of the travel advisor model. Their contributions helped maintain the integrity of the data-driven approach throughout the project.

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