THE ALGORITHM EFFECT: HOW AI-DRIVEN TRAVEL PLANNING FUELS OVERTOURISM

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Abstract
Artificial intelligence (AI) is increasingly shaping tourist decision-making through recommendation systems embedded in travel platforms, search engines, and conversational AI models. This study examines how AI-generated travel recommendations contribute to overtourism by reinforcing the popularity of crowded destinations. Using an experimental approach, various GPT models were prompted to suggest travel destinations within selected regions of the Czech Republic. The results revealed a strong bias toward well-established tourist hotspots, many already experiencing overtourism-related challenges. Lesser-known locations, which could serve as alternative destinations to distribute tourist flows more evenly, were rarely recommended. These findings suggest that AI-driven travel planning, rather than diversifying visitor distribution, may amplify existing tourism imbalances by favouring destinations with high digital visibility and historical popularity. This study highlights the need for more responsible AI design in tourism applications to promote sustainable travel behaviours and mitigate overtourism.

Key words: AI-Driven Travel Recommendations, GPT Models in Tourism, overtourism, data-driven travel choices, tourism sustainability

Introduction

Today's young travellers increasingly rely on AI-powered tools rather than traditional travel guides when choosing destinations. With instant access to AI chatbots, recommendation algorithms, and personalised travel apps, they can receive tailored suggestions based on real-time trends, social media influence, and user preferences. Unlike static book guides, AI offers dynamic, interactive, and up-to-date recommendations that require prior research and may contain outdated information. This shift reflects a broader trend toward digital convenience, where AI-driven insights shape travel decisions more efficiently than conventional sources, reinforcing the appeal of well-known, high-visibility destinations.

Artificial Intelligence (AI) represents a vast field encompassing systems that emulate human cognitive functions, including reasoning, decision-making, and learning from past experiences. AI technologies can be categorised into various types, notably narrow or weak AI, which focuses on specific tasks, and general or strong AI, which exhibits broader, human-like intelligence capabilities (Tang et al., 2022; Ramli et al., 2023).

Generative Pre-trained Transformer (GPT) models are a subset of AI designed for natural language understanding and generation. These models, such as the latest iterations of GPT-4, leverage deep learning techniques to predict and generate coherent text sequences based on input data. The unique architecture of GPT models allows them to understand context, making them highly effective for various applications, including conversation, content creation, and even trip planning (Zheng et al., 2023). Their ability to produce nuanced language mimics human creativity and opens up numerous possibilities, significantly enhancing human-computer interactions across multiple sectors (Bryndin, 2019).

GPT generates responses using a probabilistic approach based on its training data. When asked to recommend travel destinations, the model follows these steps:

1. Pattern recognition: It analyses the input prompt and identifies relevant keywords, such as a region or type of attraction.
2. Data retrieval and association: GPT doesn't access real-time databases (although some of the latest ones already allow this), so it relies on its pre-trained knowledge to recall well-known locations associated with the input.
3. Probability-based selection: The model predicts the most likely words and phrases that would logically follow, often favouring well-documented, frequently mentioned destinations.
4. Bias toward popularity: Because the training data consists of widely available sources (news articles, travel blogs, and guidebooks), GPT prioritises destinations with high digital visibility, reinforcing existing tourism patterns.

This process explains why GPT-based travel recommendations often favour already popular locations, inadvertently contributing to overtourism. This article aims to determine (1) whether the assumption of preferring overtourism-affected locations is valid, (2) how the results differ for different types of GPT, and (3) to assess to what extent the use of GPT when choosing a travel destination will affect the situation with overtourism in these destinations.

Materials and methods

The research experiment was conducted using the website https://editee.com/chat-gpt, which provides free access to eight different GPT models (see Fig. 1).

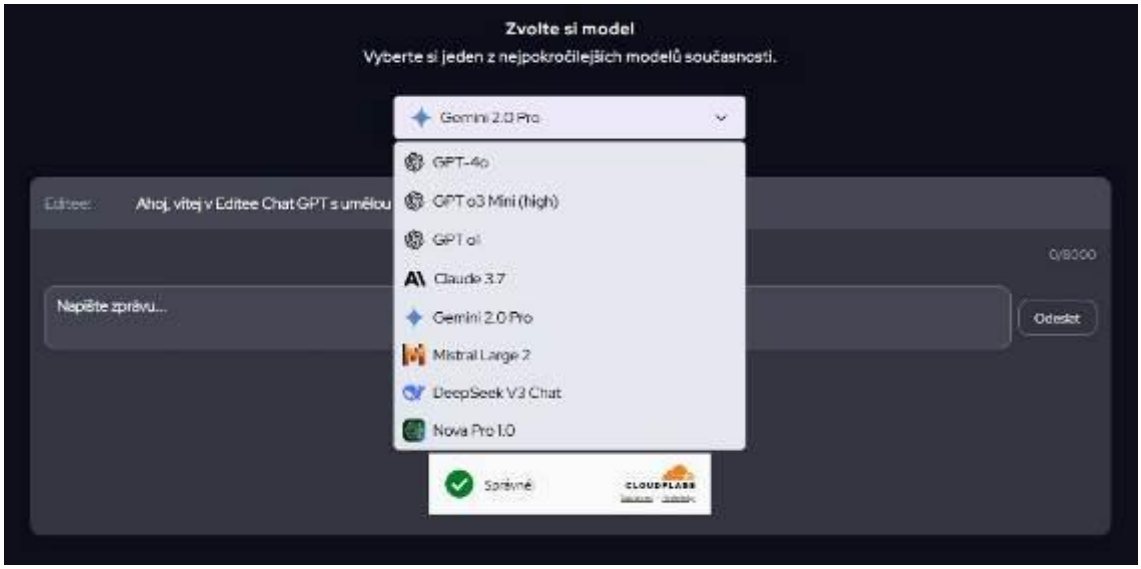

Fig. 1: Interface used for asking questions on Editee.com

Five selected models, GPT-4o, GPT o1, Claude 3.7, Gemini 2.0 Pro, and Mistral Large 2, were used for comparison. The experiment was conducted on 84 volunteers in a university classroom, who were gradually asked to answer the following two questions using the selected GPT model:

What locations would you recommend I visit in (selected region)?

Are there any interesting locations in (selected region) that are not so crowded?

The following regions were selected: Bohemian Paradise, Krkonoše Mountains, Bohemian Switzerland, Prague, and South Moravia. Each volunteer recorded the survey results on a shared Google document, after which the responses were computer-processed. A new conversation was always created when testing a new model.

Results

The result of the above experiment was a list of locations and their frequency. Subsequently, an assessment was made of whether the locations really exist and are located in the selected region—in which case, the answer was evaluated as correct. If the location existed but was not in the selected region, the answer was evaluated as "bad advice." If it was a non-existent location, the answer was evaluated as "non-existent place."

Tab. 1 shows the results for the GPT-4o model. Only correct answers are listed in the table. The results show that this model can recommend the most famous destinations in the selected regions very well, slightly worse than destinations with fewer tourists. The model achieved worse results in the Krkonoše Mountains, where the overall attraction is a stay in the mountains, not just selected highlights. Overall, however, it can be said that most locations in the "top" destinations are affected by overtourism, and in some cases, also in the "not so crowded" destinations. For the second category, there is a greater variance in the answers.

Tab. 1: Polling results for the GPT-4o model. Only correct answers are shown.

Region	Most frequently recommended "top" destinations (N of responses)	Most recommended "not so crowded" destinations (N of responses)
Bohemian Paradise	Prachovské skály (84), Hruboskalsko (83), Trosky Castle (83), Kost Castle (82), Valdštejn Castle (78)	Příhrazské skály (65), Plakánek (63), Kozákov (61), Vyskeř (60), Klokočské skály (58)
Krkonoše Mountains	Sněžka (84), Pančavský vodopád (82), The Source of the Elbe River (82), Luční bouda (78), Harrachov (77)	Klínové Boudy (55), Krásná Pláň (53), Černá Hora (53), Rýchory (51), Pomezní hřeben (48)
Bohemian Switzerland	Pravčická brána (84), Edmundova soutěska (84), Divoká soutěska (84), Mariina Skála (82), Šaunštejn (82)	Kyjovské údolí (74), Brtnické ledopády (72), Růžovský vrch (58), Vlčí hora (57), Zadní Jetřichovice (52)
Prague	Prague Castle & St. Vitus Cathedral (84), Charles Bridge (84), Old Town Square & Astronomical Clock (84), Jewish Quarter (83), Vyšehrad (81)	Vyšehrad (75), Nový Svět (73), Valdštejnská zahrada (73), Břevnov Monastery (72), Náplavka (72)
South Moravia	Lednice-Valtice Cultural Landscape (84), Pálava (84), Moravian Karst (84), Brno (84), The Battlefield of Austerlitz (81)	Pasohlávky & Mušov Lakes (71), Rosa Coeli Monastery (70), Tišnov (65), Šardice & Mutěnice Wine Cellar Alleys (64), Milotice Château (64)

Tab. 2 shows the results of comparing the individual models with each other. In general, it can be said that the recommended locations were very similar for all models; only the frequencies and the number of recommended locations differed slightly. However, the comparison in the "bad advice" and "non-existent place" categories is interesting, where the GPT o1 model achieved significantly the worst results, which is considered (in March 2025) one of the most advanced GPT models, capable of verifying information and critically evaluating it. However, its results had the lowest proportion of correct answers. A higher error rate was recorded for all models for the query on "not so crowded" destinations. Given that less information about these destinations is available, unlike the well-known highlights, the models made more errors in their answers.

Tab. 2: Comparison of correctness of answers for tested GPT models

GPT model	"Top" destinations		"Not so crowded" destinations	
	Bad advice	Non-existent place	Bad advice	Non-existent place
GPT-4o	9%	3%	24%	12%
GPT o1	26%	43%	23%	62%
Claude 3.7	12%	2%	20%	6%
Gemini 2.0 Pro	22%	1%	25%	4%
Mistral Large 2	10%	1%	19%	1%

However, GPT models have made great progress in recent years and months, and their advice, with some errors, was correct and usable in practice. Therefore, it can be expected that GPT will be used more extensively in travel planning in the future.

Discussion and Conclusion

When critically evaluating the results, it should be noted that (1) the assumption of preferring overtourism-affected locations was confirmed. When we compare the locations recommended by the

GPT models, most of the "top" locations are overtourism-affected (compare, for example, the results for the Bohemian Paradise with Drápela 2023). Even some locations that are supposed to be "not so crowded" are actually affected by overtourism, or they definitely cannot be described as quiet and with a small number of tourists.

When comparing (2) the results for different GPT models, it can be said that although there are significant differences between the models, their level (except GPT o1) is very good for possible real-life use. Moreover, the models are constantly evolving, and their innovative versions are being created, so the results will be outdated by the time of publishing this article. The worse results for the GPT o1 model may be caused by accessing the model through the Editee.com website, but the implementation of the experiment was not possible through the ChatGPT model homepage because, at the time of the experiment, the o1 model was paid.

And how to answer the third research question (3)? To what extent the use of GPT when choosing a travel destination will affect the situation with overtourism in these destinations? Given the mechanism of generating results in GPT models and the above-mentioned experimental results, the hypothesis of a potential worsening of the situation with overtourism in the most popular destinations can definitely be confirmed.

These results correlate with the findings of other authors. Recommendations generated through AI can create herd-like behaviour among tourists, as they follow popular suggestions without considering the local context or potential impacts (Dias et al., 2021). Without responsible implementation and constant monitoring, deploying GPT models in travel can lead to a lack of balance between promotion and preservation. Incorporating risk communication strategies into the functionalities of travel AI, as emphasised by Choe and Kim, could mitigate adverse impacts by ensuring that resources are prioritised to maintain the integrity of destinations while catering to tourist interests (Choe & Kim, 2021).

Moreover, while these models can aid in planning by personalising the travel experience, they may inadvertently contribute to negative perceptions of specific destinations, especially if these suggestions are accompanied by narratives that glorify over-touristed sites (Choe & Kim, 2021). For instance, during the COVID-19 pandemic, it was noted that safety perceptions heavily influenced tourists' travel behaviours, illustrating how messaging around travel advice can lead to increased traffic to certain locations at high risk of overtourism (Rahman et al., 2021).

In conclusion, while GPT models hold the potential to revolutionise travel planning by streamlining processes and personalising experiences, their indiscriminate use could significantly contribute to overtourism, necessitating the implementation of measures aimed at sustainable tourism management.

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Souhrn

Umělá inteligence (AI) stále více formuje rozhodování turistů prostřednictvím systémů doporučení zabudovaných do cestovních platforem, vyhledávačů a velkých jazykových modelů (GPT). Tato studie zkoumá, do jaké míry přispívají cestovní doporučení generovaná AI k overturismu tím, že posilují

popularitu již tak přeplněných destinací. Experimentálním přístupem byly různé modely GPT vyzvány, aby doporučily ve vybraných regionech Česka turistické cíle. Výsledky odhalily silnou preferenci dobře zavedených turistických hotspotů, z nichž mnohé již čelí problémům souvisejícím s overturismem. Méně známé lokality, které by mohly sloužit jako alternativní destinace pro rovnoměrnější rozložení turistických toků, byly doporučovány jen zřídka. Tato zjištění naznačují, že plánování cestování řízené AI může zesílit stávající nerovnováhu v cestovním ruchu upřednostňováním destinací s vysokou digitální viditelností a historickou popularitou. Tato studie zdůrazňuje potřebu zodpovědnějšího návrhu AI v aplikacích cestovního ruchu s cílem podporovat udržitelné cestovní chování a zmírňovat projevy overturismu.

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