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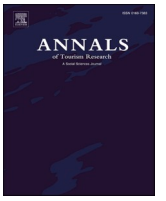

Research note

Customized language models for tourism management: Implications and future research

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Sitting at the intersection between social and computer sciences, human-computer interaction research focuses on understanding human behavior in relation to computer systems (Olson & Olson, 2002). Having seen many developments over the years, human-computer interaction has been a focal point in sector-specific research, including in tourism management (Stankov & Gretzel, 2020; Tung & Law, 2020). Recently, attention has been given to human-artificial intelligence interaction in particular. For instance, Lu et al.'s (2019) Service Robot Integration Willingness Scale and Gursoy et al.'s (2019) Artificially Intelligent (AI) Device Use Acceptance model explore guests' willingness to accept different types of AI in tourism contexts, while Fu et al. (2022) have put forward the Robot Usage Resistance model to explain tourism employees' reasons for resisting the use of robots.

Most recently, user interfaces based on large language models have rapidly grown in popularity (Shanahan et al., 2023). Language model based consumer products, such as ChatGPT or Gemini, offer tourism companies new ways of working (Tuomi, 2023). For instance, Expedia recently launched language model based trip-planning tools (Biesiada, 2023), InterContinental Hotels Group is building a similar tool to improve booking experience (IHG, 2024), while Air Canada made headlines when their language model offered tourists discounts that did not exist (Garcia, 2024). Importantly, the potential for so called 'generative artificial intelligence' goes beyond major tourism corporations or tourist-artificial intelligence interaction. New tools facilitate the construction and sharing of Custom Assistants – customized versions of popular large language models – at a click of a few buttons, providing new affordances for tourism businesses and other stakeholders by facilitating new types of human-computer interaction in tourism, including tourist-artificial intelligence, employee-artificial intelligence, business-artificial intelligence and policymaker-artificial intelligence.

Previous research on human-computer interaction has focused e.g. on user interface design, leveraging e.g. Cognitive Load Theory (Hollender et al., 2010), Activity Theory (Clemmensen et al., 2016), or theories of Social Presence (Tussyadiah et al., 2018). Similarly, researchers have used various approaches to study human-artificial intelligence interaction in tourism, such as pro-sustainable

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behavioral nudges for tourists (Tussyadiah & Miller, 2019) or the psychological factors impacting humanoid robot adoption in hospitality (Tuomi et al., 2021). However, given the rapid development and deployment of customized language models, there is a pressing need for new social science theories for understanding human-AI interaction in the context of language models.

To offer empirical evidence on the impacts of and potential for customized language models for tourism, two example Assistants were developed using OpenAI's GPTBuilder in February 2024. Both Assistants were co-developed with 21 tourism management students and qualitatively tested by 78 tourists using a combination of a design sprint and iterative testing. GPTBuilder allows users to choose a name for the Assistant, define behavioral instructions it should follow, link to external applications, and upload a custom knowledge-base for the Assistant to prioritize when responding to prompts.

The first Assistant was developed for tourists traveling to a relatively unknown destination. The Assistant was tasked to promote destination-specific food traditions and customs. The Assistant's knowledge-base consisted of 958 pages of open-access text in three languages about the target destination's food culture, along with information about current events in the area. The second Assistant was developed for a boutique hotel to train their seasonal employees. The knowledge-base consisted of contextual information about the venue, its history and service principles, e.g. food offering, allergens, wine pairings, ancillary services, etc. Both Assistants were tested using an open-ended talk aloud methodology. The average interaction time with each assistant was 4 min (21 messages), and the qualitative data was recorded, transcribed, and analyzed thematically.

Three key themes were identified. First, the importance of structuring the Assistants' behavioral instructions or its 'system prompt', such as tone-of-voice, response length, or topics to avoid, was noted. The more complex the Assistant use-case is, the more complex its behavioral instructions should be. We suggest narrow use-cases and repeating the most important behavioral instructions multiple times. Second, the size of Assistants' knowledge-base should reflect its intended use-case. Simply adding more contextual information might not lead to better results. The knowledge-base should be concise, well-curated and signposted via notes, headings or use of knowledge graphs to steer the language model. Third, the balance between memorization (the Assistant parroting content from its knowledge-base) and hallucination (the Assistant going 'off-script') should be carefully considered based on the use-case. Especially for business-critical cases the Assistant should cite its knowledge-base to signpost its output. Overall, an iterative approach with multiple rounds of testing and red-teaming, i.e. purposefully testing the limits of the Assistant, is suggested.

Customized language models facilitate new types of human-computer interaction in tourism. Adopting a hybrid-augmented

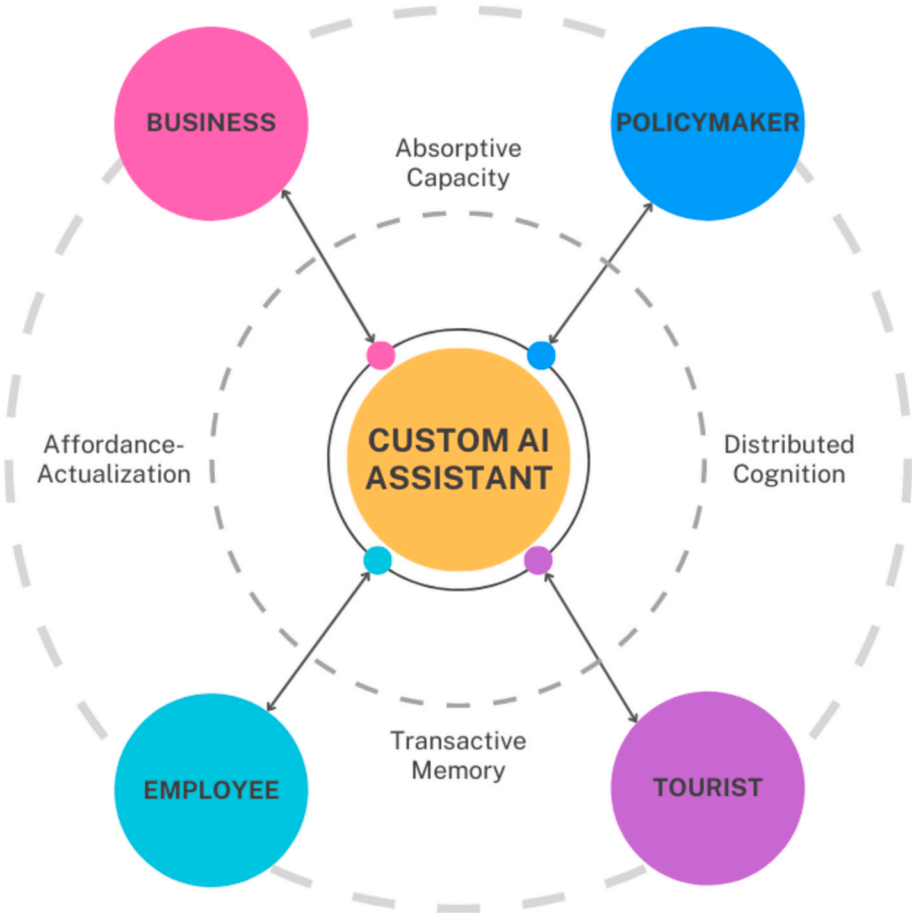

Fig. 1. Human-Computer Interaction facilitated by Customized Language Models.

intelligence view on human-artificial intelligence interaction (Zheng et al., 2017), these can be mapped across four dimensions of interaction between the Custom Assistant & tourist, employee, business, policymaker (Fig. 1). Hybrid-augmented intelligence posits that the combination of humans and technology can result in systems that leverage the strengths of both to achieve outcomes neither could accomplish alone, i.e. integrate the nuanced understanding, emotional intelligence, and ethical reasoning of humans with the computational efficiency, data processing and pattern recognition of artificial intelligence (Wilson & Daugherty, 2018). For customized language models, this means that managers need to figure out the use-cases in their field where an Assistant is likely to give 'good-enough' answers to help allocate domain experts' attention to where it matters most.

In terms of Tourist-Assistant interaction, Assistants offer a new way for tourists to experience a novel destination before-during-after their trip (Dwivedi et al., 2024). To capitalize on this, tourism marketers should spearhead a move from traditional search engine optimization to Assistant-optimized marketing. Potential theoretical base for further exploring this could be e.g. the theory of Distributed Cognition. For Employee-Assistant interaction, a key use-case is that Assistants introduce new ways for employees to be trained and onboarded, as opposed to traditional training manuals. Given the seasonal nature of tourism in many destinations, embedding the context specific knowledge of a particular business into an Assistant could afford tourism employees to move from delivering service to staging an experience (Tussyadiah, 2013). This type of interaction could be further explored e.g. by utilizing Transactive Memory theory.

When it comes to Business-Assistant interaction, Assistants offer businesses new ways to scale-up their marketing & sales by facilitating multilingual customer support, as the knowledge-base of an Assistant can be in a different language than the end-user prompt or model output. For example, Klarna (2024) has reported how their Assistant is able to do the equivalent work of 700 customer service representatives. This research area could be further explored by e.g. Affordance-Actualization theory. Finally, for Policymaker-Assistant interaction, Assistants offer new tools for understanding the complexity of tourism policymaking (Crabolu et al., 2023). Given the multidisciplinary nature of tourism, Assistants may help highlight synergies between different domains of knowledge, such as overlapping or contending regulatory frameworks. The theory of Absorptive Capacity could be useful to guide further studies (Table 1).

This research presents preliminary findings and future research ideas for exploring the potential of customized language models in

Table 1
Implications for tourism research.

Interaction with customized language model	Example	Example expected outcome	Example theory	Example methodology	Example research questions
Tourist	Destination-specific travel planning	From SEO to Assistants-optimized content strategies	Distributed Cognition	Experimental studies, behavioral economics	How do collaborative interactions between tourists and Assistants influence decision-making? What impact does Assistant-mediated communication have on destination image and loyalty? How effective are Assistant-driven interventions in changing behavior?
Employee	Context-specific training for seasonal workers	Surfacing tacit knowledge, improved retention and productivity	Transactive Memory	Ethnography, field studies, usability tests	What roles do Assistants play in enhancing or disrupting established knowledge-sharing/learning practices at workplaces? How does reliance on Assistants for information affect teamwork, e.g. problem-solving, innovation, productivity, workplace solidarity? What training and skills are required for tourism employees to effectively collaborate with Assistants?
Business	Multilingual marketing and sales support	Upselling, hyper-personalization, labor cost reduction	Affordance-Actualization	Econometrics, user adoption studies, cost-benefit analyses	How do different types of tourism businesses vary in their ability and approach to integrating Assistants into their processes? What barriers prevent the actualization of Assistants' affordances in tourism? How do businesses measure the success of Assistant integration into operations?
Policymaker	Data-driven discovery	Understanding synergies between domains of knowledge	Absorptive Capacity	Simulation, knowledge management studies	What are the challenges of integrating Assistants into policymaking? How do interactions with Assistants influence policy evaluation and revision? How do Assistants impact the accountability & traceability of policymaking?

tourism. While offering early insight, limitations should be noted. We report on two examples, both with small samples and limited use-case contexts. Stemming from this, the theoretical contribution of this study is preliminary. We call for tourism researchers to build on and expand our findings by combining different methodological approaches and sampling strategies. Particularly interesting might be exploring interconnected Assistants or multimodal AI. It should also be noted that language model based Assistants are not the only novel form of human-computer interaction in tourism. Others include brain-computer interfaces and AI-powered wearable devices, e.g. smart glasses. There is a general need for more research on human-computer interaction in tourism contexts.

CRediT authorship contribution statement

Aarni Tuomi: Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Iis Tussyadiah:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Mário Passos Ascenção:** Writing – review & editing.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability

The data that has been used is confidential.

References

Biesiada, J. (2023). Expedia and booking are putting AI through its paces. https://www.travelweekly.com/Travel-News/Travel-Technology/Expedia-and-Booking-putting-AI-through-paces.
Clemmensen, T., Kaptelinin, V., & Nardi, B. (2016). Making HCI theory work: An analysis of the use of activity theory in HCI research. *Behaviour & Information Technology, 35*(8), 608–627.
Crabolu, G., Font, X., & Eker, S. (2023). Evaluating policy complexity with causal loop diagrams. *Annals of Tourism Research, 100*, Article 103572.
Dwivedi, Y., Pandey, N., Currie, W., & Micu, A. (2024). Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: Practices, challenges and research agenda. *International Journal of Contemporary Hospitality Management, 36*(1), 1–12.
Fu, S., Zheng, X., & Wong, I. (2022). The perils of hotel technology: The robot usage resistance model. *International Journal of Hospitality Management, 102*, Article 103174.
Garcia, M. (2024). What air Canada lost in 'remarkable' lying AI chatbot case. https://www.forbes.com/sites/marisagarcia/2024/02/19/what-air-canada-lost-in-remarkable-lying-ai-chatbot-case/.
Gursoy, D., Chi, O., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157–169.
Hollender, N., Hofmann, C., Deneke, M., & Schmitz, B. (2010). Integrating cognitive load theory and concepts of human-computer interaction. *Computers in Human Behavior, 26*(6), 1278–1288.
IHG. (2024). IHG builds a new travel planner. https://www.ihgplc.com/en/news-and-media/news-releases/2024/ihg-hotels-and-resorts-builds-a-new-travel-planner-powered-by-google-cloud-ai.
Klarna. (2024). Klarna AI assistant handles two-thirds of customer service chats in its first month. URL: https://www.klarna.com/international/press/klarna-ai-assistant-handles-two-thirds-of-customer-service-chats-in-its-first-month/.
Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot willingness scale. *International Journal of Hospitality Management, 80*, 36–51.
Olson, G., & Olson, J. (2002). Human-computer interaction: Psychological aspects of the human use of computing. *Annual Review of Psychology, 54*, 491–516.
Shanahan, M., McDonell, K., & Reynolds, L. (2023). Role play with large language models. *Nature, 623*, 493–498.
Stankov, U., & Gretzel, U. (2020). Tourism 4.0 technologies and tourist experiences: A human-centered design perspective. *Information Technology & Tourism, 22*, 477–488.
Tung, V., & Law, R. (2020). The potential for tourism and hospitality experience research in human-robot interactions. *International Journal of Contemporary Hospitality Management, 29*(10), 2498–2513.
Tuomi, A. (2023). AI-generated content, creative freelance work and hospitality and tourism marketing. In B. Ferrer-Rosell, D. Massimo, & K. Berezina (Eds.), *Information and communication Technologies in Tourism 2023*. Cham: Springer.
Tuomi, A., Tussyadiah, I., & Hanna, P. (2021). Spicing up hospitality service encounters: The case of pepper™. *International Journal of Contemporary Hospitality Management, 33*(11), 3906–3925.
Tussyadiah, I. (2013). Toward a theoretical foundation for experience design in tourism. *Journal of Travel Research, 53*(5), 543–564.
Tussyadiah, I., & Miller, G. (2019). Nudged by a robot: Responses to agency and feedback. *Annals of Tourism Research, 78*, Article 102752.
Tussyadiah, I., Wang, D., Jung, T., & tom Dieck, M.C.. (2018). Virtual reality, presence, and attitude change: Empirical evidence from tourism. *Tourism Management, 66*, 140–154.
Wilson, J., Daugherty, P. (2018). Collaborative intelligence: How humans and AI are joining forces. https://hbr.org/2018/07/collaborative-intelligence-humans-and-ai-are-joining-forces.
Zheng, N., Liu, Z., Ren, P., Ma, Y., Chen, S., Yu, S., … Wang, F. (2017). Hybrid-augmented intelligence: Collaboration and cognition. *Frontiers of Information Technology & Electronic Engineering, 18*, 153–179.

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