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Tourists and Artificial Intelligence-LLM Interaction: The Power of Forgiveness

Abstract

Artificial intelligence large language models (AI-LLMs) can become valuable travel advisors but often suffer from hallucinations that can diminish consumers' confidence in their results. This study explores the relationship between tourists and AI large language model interactions by analyzing how (i) attachment-aversion affects the motivational strength for using AI large language models as travel advisors and (ii) the moderation role of forgiveness in the relationship between the symbolic benefits consumers get from using those AI advisors and the attachment-aversion relationship. A sample of 451 participants in a Qualtrics survey was used to test the conceptual proposed framework. Findings reveal the important role of enriching the self and enticing the self in shaping attachment-aversion relationships. Forgiveness strengthens the relationship between enriching the self (symbolic benefits) and attachment-aversion. This research can guide managers in using its findings to develop customized AI-LLMs that foster engaging dialogues with travelers, enhance feelings of attachment, and forgive any potential missteps throughout the relationship.

Keywords

Attachment-Aversion relationship, Large Language Models, Tourists- AI-LLMs, Motivational strength, Forgiveness

1. Introduction

Artificial intelligence (AI) has become an integral part of our lives. Its applications have impacted various aspects, such as how we work, think, and travel (Pentina et al., 2023). The tourism industry – which depends on creating exceptional and seamless experiences for tourists – has long recognized the need to study the implications that technology, and more particularly, human-to-machine interactions may play in the growth of the global tourism industry (Shin & Kang, 2023). Despite the importance of AI in Tourism, the recent emergence of AI-Large Language Models (AI-LLMs) (e.g., ChatGPT) and their potential to replace more common ways to find travel destinations also brought some

concerns regarding the accuracy of these AI systems. It is recognized that AI-LLMs suffer from hallucinations and fabrications (Emsley, 2023), leading to inaccurate results when assisting tourists on their travels. While this type of AI virtual assistant can play a very important role in hospitality and tourism, it is essential to understand how consumers are willing to create a bond with them over time and whether they can forgive erroneous recommendations.

According to Statista (2023a), the revenue of the virtual assistant market (e.g., chatbots) is expected to increase from around 370M€ in 2017 to over 2B€ in 2024. This indicates that the market has grown more than fivefold in the last seven years. Additionally, Statista (2023b) reports that 76.9% of tourists in 2022 were interested in staying at hotels that offer chatbots, which suggests that tourists are looking for new experiences that allow them to use technology to assist with their travel requirements.

Scholars have recently studied the acceptance of chatbots in the hospitality and tourism industry. For instance, Pillai and Sivathanu (2020) used technology acceptance models and anthropomorphism to explore the factors influencing tourists' behavioral intention and actual usage. Similarly, Mélian-González et al. (2021) found that chatbot performance, habit, anthropomorphism, and the inclination to use self-serving technologies affect the intention to use this technology. Orden-Mejía and Huertas (2022) investigated tourists' satisfaction with chatbots during their travel journey and identified informativeness, empathy, and interactivity as the most significant factors that influence travel satisfaction. Zhang et al. (2023), however, analyzed the acceptance of chatbots in the tourism industry by using the unified theory of adoption and use of technology (UTAUT2), the theory of perceived risk, personalization, and anthropomorphism, and highlighted the negative impact of privacy risks on adoption. Others explored the engagement and recovery behaviors in AI and virtual environments (Yin, Li, & Qiu, 2023;

Jia, Yao, & Fan, 2023). Finally, Zhang et al. (2024) studied the effect of emotional expressions of chatbots on customer satisfaction in the tourism industry.

Although the findings are interesting, the advent of ChatGPT (an AI large language model) has highlighted the importance of elucidating the impact of interacting with such systems on tourist behavior. AI large language models can interact in a much more human-like way than previous chatbots, making it a transformational technology in the tourism industry. However, thus far, only a few literature review studies have focused on the implications of using AI-LLMs in tourism (Gursoy & Song, 2023; Shin & Kang, 2023), and the empirical academic focus on the topic is just at the beginning, one of such few examples being the work of Ali et al. (2023) about the antecedents and consequents of travelers' response to AI advisors recommendations. AI large language models are known to be plagued by hallucinations and fabrications (Emsley, 2023), which often create erroneous findings in how the system helps tourists in their journey. Given such issues in how AI large language models can interact with travelers, it is paramount to understand if consumers can forgive AI advisors' erroneous recommendations. To address this gap in the literature, the current paper explores tourists' relationship with AI-LLMs by using the attachment-aversion (AA) relationship theory of Park et al. (2013). Additionally, the paper explores to what extent travelers can forgive the AI-powered travel advisor and continue using it for further recommendations when poorly guided by AI large language models.

This study contributes to the field of AI in tourism by going beyond technology acceptance models and exploring the emotional dynamics between tourists and AI entities in AI large language model interactions. We explore how the benefits derived from interaction with AI-LLMs (e.g., hedonic, functional, and symbolic benefits) affect the attachment-aversion relationship and, thus, influence the motivation to continue the

relationship in the future. The study also explored the role of forgiveness in the relationship between symbolic benefits and attachment-aversion.

The findings can have important implications for companies so that they can find a balance between technological advancements and user satisfaction. To achieve this, the current study proposes the following research questions: (1) how does experience with AI-LLMs affect attachment (aversion) and the motivation to continue the relationship in the future? (2) can consumers forgive AI advisors' advice when they make a mistake? The results of this research can help train and orient tourism professionals on how to integrate AI tools seamlessly while avoiding any potential pitfalls that can erode attachment and increase aversion in the traveler's relationship with the brands.

2. Literature review and hypotheses development

The attachment-aversion (AA) theory – initially proposed by Park et al. (2013) and further developed by Schmitt (2013) – is a crucial framework for understanding the relationship between consumers and brands. The AA theory is based on Fournier's (1998) anthropomorphic perspective of the customer-brand relationship, the interdependency theory (Thibaut & Kelly, 1959), and the attraction theory (Aron & Aron, 1986). This theory suggests that a consumer's motivation to form a bond with a brand depends on their interaction with the brand and the level of emotional connection. Several studies argued that humans can develop emotional attachments toward various entities. These entities include animals, locations, unique objects, brands (Ahuvia, 2005), and even human brands or celebrities (Thomson, 2006). AI [large language models](#) (e.g., ChatGPT) that possess human-like qualities are known for creating a sense of loyalty in consumers similar to human relationships. Thus, AI-powered travel assistants based on large language models are seen as more than just products (Niu & Mvondo, 2024). They

embody anthropomorphic traits akin to brands (Pham et al., 2024). Consequently, it is expected that emotional attachment can also form between consumers and AI-LLMs.

According to the [attachment-aversion](#) theory, establishing an experience with a brand is essential for creating a future relationship between the consumer and the brand. Therefore, the experience a customer has with a brand can create a relationship that is either positive (attachment) or negative (aversion). This relationship depends on how closely the customer identifies with the brand (brand-self distance) and how well-known the brand is (brand prominence), but it can also influence the customer's level of motivation (motivational strength). The level of motivational strength determines whether they continue using the product or service (approach), maintain the brand relationship over time (maintenance), and potentially strengthen it in the future (enhancement). In this vein, we argue that the relationship between AI-LLMs and humans is similar to that of brands and humans, in light of [the attachment-aversion](#) theory.

2.1. Antecedents of attachment-aversion relationship with AI-LLMs

The determinants of AA (attachment-aversion) relationship with AI-powered travel assistants based on large language models can be aggregated into three aspects, representing hedonic, functional, and symbolic benefits. AI-LLMs are expected to interact like brands in their relationships with humans due to their human-like qualities and the ability of humans to extend their self to things, animals, objects, or technologies (Belk, 2016; Schmitt, 2013). Therefore, the first determinant is represented here by “enticing the self”. Enticing the self (hedonic benefit) is the element connected to the sensory aspects of the experience (Oh et al., 2019). When tourists interact with AI-LLMs, the language, answers, and overall politeness can create a sense of appeal and attract them to continue the interaction.

The second determinant (functional) is represented by “enabling the self”. An AI-large language model should enable the self when it meets customers' goals effectively (Oh et al., 2019; Park et al., 2013). In the case of AI [large language models](#), they are known to enhance consumers' ability to search for accurate information and to speed up their performance. Indeed, ChatGPT has been noted for its agility in generating contextually relevant responses promptly (Lian et al. in 2024) and in presenting precise information (Javaid et al., 2023). More specifically, AI-LLMs (e.g., ChatGPT) have been successfully used as a tourist information search strategy (Pham et al., 2024). AI [large language models](#) contribute to tourists feeling empowered and efficient as they provide quick and accurate information that helps consumers achieve their goals, thus enabling them.

Finally, the last determinant (symbolic) can be represented by “enriching the self”. The relationship with AI-LLMs can enhance the tourist experience by enriching their sense of self. Enriching oneself involves representing the past, present, or ideal future self, internally or externally, to please the spiritual self (Escalas & Bettman, 2005). A tourist can have a more enriched experience by interacting with AI-based recommendations that express their identity, represent their preferences, and reinforce their values. In AI large language models with user memory, personalized recommendations can be made based on past experiences and self-identity, which can enrich the self as suggested by Park et al. (2013). When a tourist sees that the AI-powered travel assistant characteristics express who he/she is or wants to be as a person, then the tourist can extend the self to such a powered language model (Belk, 2016). AI [large language models](#) can even reinforce the deepest values of the tourist through the language used to communicate. However, the opposite can also occur, that is, the relationship with the AI large language models may not be sensory, enthusiastic, or efficient, or the tourist

may not identify him/herself with what it represents or transmits. In this case, it is expected that the tourists develop an aversion.

AI [large language models](#) have many benefits that are relevant to the self and can operate as partners in a relationship (Fournier, 1998). The most cited are functional uses, from solving problems such as programming bugs (Surameery & Shakor, 2023) to getting information and supporting individuals in making informed decisions about their health (Biswas, 2023a), getting advice on climate change actions (Biswas, 2023b), or helping tourist search for information and make informed decisions (Gursoy & Song, 2023). As a chatbot, it creates a user experience beyond the pragmatic qualities of usefulness and usability, as it appeals to a user's sense of pleasure through stimulating experiences (Skjuve, Følstad, & Brandtzaeg, 2023). AI [large language models](#) may have symbolic benefits, as students who demand novelty had stronger trust-based relationships with AI-powered assistants based on large language models than those who did not (Tiwari et al., 2023). Thus, we expect that AI-LLMs enrich the self of the partner by pleasing his/her spiritual self because of the novelty and all the symbolic representations (Escalas & Bettman, 2005) that AI [large language models](#) represent. The symbolic fascination can even lead the human partner to strengthen the attachment-aversion relationship, regardless of whether the AI-LLMs are wrong or not.

As the attachment-aversion framework is focused on a self-based customer-brand relationship, we predict that the most influential determinant that will drive the process will be the symbolic element (the enriching the self) as it represents the tourist's symbolic meaning of the relationship between AI large language models and the individual self (see Figure 1). Thus, we predict:

H1: The 3Es the self, (a) enriching, (b) enticing, and (c) enabling, contribute to enhancing the AA relationship with AI-LLMs.

-- INSERT FIGURE 1 HERE --

2.2. Attachment-Aversion relationship with AI-LLMs

AI [large language models](#) are a novel technology poised to have promising applications for hospitality and tourism (Gursoy & Song, 2023). Unlike other virtual assistants – such as Alexa or Google Home – AI-LLMs can respond to users’ prompts in a much more engaging way and use a dialog similar to that of a human being, which can promote a much stronger relationship (Pham et al., 2024). Indeed, the self-extension theories by Belk (2016), which were applied to digital intangible entities, imply that consumers assimilate products, individuals, brands, and even intangible items into their self-identity and utilize them as a vehicle for self-extension. In the context of AI large language models – where the level of proficiency can equal or even exceed human capabilities – this extension could potentially result in self-expansion, enhancing the user's abilities (e.g., to search better for information about a destination). Hoffman and Novak (2018) introduced a model of consumer-object interrelation where the consumer’s experience (for instance, their ability to perceive their surroundings and make unique human interpretations) and the object’s experience – represented here by [AI-LLMs](#) (for example, its ability to interpret scattered information with numerous parameters) – can complement each other to achieve satisfaction and proficiency levels that would be unattainable without this interrelation (Hoffman & Novak, 2018).

According to Guerreiro and Loureiro (2023), tourists can develop a sense of attachment or aversion toward AI-embedded virtual assistants, which suggests that the same feelings can be developed regarding AI-powered travel assistants based on large language models (e.g., ChatGPT), particularly when using [AI-LLMs](#) as a travel guide to help them decide on the best destination and route to choose. Attachment occurs when tourists find [AI-LLMs](#) meaningful to themselves, while aversion happens when they

perceive it as a threat to their self-identity, creating a sense of distance (Pichierri, Petruzzellis & Passaro, 2023). Attachment and aversion exist on opposite poles of a relational spectrum, which can change over time.

Initially, the attachment-[aversion](#) (AA) framework was an integrative approach to understanding the self-based relationship between customers and brands. The current study extends this framework to the customers and [AI-LLMs](#) relationship. [Attachment-aversion](#) framework assumes that customers perceive objects as if they are humans and form relationships with them (Schmitt, 2013). The framework suggests that humans are motivated to include a brand, or now [AI-LLMs](#), in their self-concept, to enhance their ability to achieve their goals (Park et al., 2013). The attachment-aversion (AA) relationship has two dimensions, self-distance and prominence (Park et al., 2010; Park et al., 2013). Self-distance can refer to how far the tourist feels from AI-LLMs. Consumers feel closer to AI-embedded agents (e.g., chatbots) when their identities overlap, reducing the sense of self-distance between the user and the AI-agent (Kull et al., 2021). In the case of AI-powered travel assistants, if the tourist does not value the emotional and cognitive features of the assistant, the impact of the assistant's recommendations may diminish, due to the user's indifference. Prominence, however, refers to how accessible a brand is in the consumers' minds (Park et al., 2010). As brand salience increases, it becomes more accessible in consumers' memory and connected to personal experiences (Gill-Simmen et al. 2018). In the current study, we suggest that if AI-LLMs are emotionally and cognitively relevant to the tourist, they are more likely to create strong memories associated with them. Negative memories associated with AI-LLMs can also lead to prominence in tourists' minds, but those memories will be negative and will lead to avoiding AI-LLMs.

Motivational strength reflects, in the context of the customer and AI-powered travel assistant relationship, the extent to which consumers are inclined to connect to AI-LLMs. This engagement stems from a robust attachment-aversion (AA) relationship, as claimed by Park et al. (2013). The motivational strength has three levels of intensity, namely approach-maintenance-strengthening. Regarding the approach and following previous literature, we suggest that travelers will approach (vs. avoid) the AI large language models if they have a high attachment-aversion relationship with it (the AI-LLMs are easily available on their memory – high salience – and if they perceive the AI-LLMs are close to them – self-distance). According to the social response theory, humans tend to react to these types of AI assistants as human actors and, therefore, apply social rules toward them, such as approaching them when they feel closer (Nguyen et al., 2023). Indeed, consumer-perceived AI congruence – which derives from how much the AI system can be congruent with the consumer's actual or desired self – is a known key driver of engagement toward AI (Yin et al., 2023). This notion further reinforces the argument that more profound and motivated relationships can emerge from such alignment. However, motivation strength also measures if travelers are willing to maintain (rather than terminate) and strengthen (rather than destroy) the relationship with AI-LLMs in the future. A strong attachment-aversion relationship is expected to enhance the willingness to use the AI-powered travel assistant based on large language models in the future. Consumers using AI-LLMs can develop strong senses of engagement and, consequently, deeper levels of attachment, such as intimacy and love (Hollebeek et al., 2024). Therefore, we suggest that the same strong effect can happen during the traveler-AI relationship and formulated the hypothesis:

H2: AA relationship with the AI-LLMs significantly affects motivational strength.

2.3. The role of Forgiveness as a moderator

While AI [large language models](#) offer advantages in assisting tourists with improved recommendations, human partners can also perceive that relying on AI-powered travel assistants based on large language models may lead to their own detriment ([Christensen et al., 2024](#)). This perception arises from the recognition of significant mistakes made by AI-LLMs and the provision of irrelevant information. For example, AI-LLMs can suffer from hallucinations and fabrications (Emsley, 2023), which can lead tourists to make poor decisions due to incorrect information about a destination or a place. Such an effect exists because AI [large language models](#) do not possess all the information about a specific place, such as the ratings and availabilities of a hotel or the comments done by travelers about each experience, particularly about recent and up-to-date journeys. Although travelers can overcome these problems by using OpenAI plug-ins (OpenAI, 2023) such as Expedia, most travelers only have available the power of the AI-LLMs without these enhancements, which can lead to errors and undermine the relationship if travelers become aware that they are receiving inaccurate information ([Camilleri, 2024](#)). Therefore, we argue that tourists' attachment or aversion toward AI-LLMs depends on their ability to forgive mistakes and maintain the relationship.

Forgiveness in a close relationship is connected to situations of betrayal (Finkel et al. 2002), being a motivational construct (Kim & Ha, 2023) and an interpersonal process (Tsarenko, & Tojib, 2015). The act of forgiving involves concomitant aspects of a cognitive, affective, and interactional nature (McCullough et al., 1997) and can also represent the cognitive and affective reactions of consumers after observing a transgression of a company or a brand (Xie & Peng, 2009). When consumers forgive a company, they can restore a relationship when some aspect goes wrong (Fernández-Capo et al., 2017; Fetscherin & Sampedro, 2019).

In the current study, forgiveness is linked to the congruity or incongruity between the tourist and the AI-powered travel assistants based on large language model responses (Escalas & Bettman, 2005). When tourists identify themselves with the AI [large language models](#) and enrich themselves via the symbolic benefits received from the relationship (Belk, 2016; Park et al., 2013), forgiveness will not be a dramatic effort, even when AI-LLMs make transgressions (e.g., hallucinations or fabrications) (Emsley, 2023). We argue that if the tourist is more open to forgiving [AI-LLMs](#) – when it does not provide accurate (or correct) information – then the intensity with which the tourist wants to approach (vs. avoid) the relationship is strengthened, leading to the promotion of the relationship between the tourist and the AI-LLMs. Thus, we propose the following hypothesis:

H3: Forgiveness strengthens the effect between enriching the self and the attachment-aversion relationship with the AI-LLMs.

3. Methodology

3.1 Sampling and Data Collection

Data was collected through an online Qualtrics panel, to avoid any bias in terms of the location of participants. The U.S. Census was used as the target population. Participants signed up for a panel membership, and surveys were distributed via a personal dashboard. If a survey met the criteria or was a good fit based on their past answers or panel type, the survey link appeared, and they completed the survey voluntarily. Over 3,000 survey invitations were sent out, and 451 were completed between May 27 and June 12, 2023. On average, it took 9 minutes to fill out the survey. Although we used well-established scales, we conducted a content analysis with 11 expert individuals to ensure the questions were well understood. Three of them were experts in the English language, and four were experts in AI systems. Finally, four customers who represented [AI-LLMs](#) users were

invited to give feedback about whether the initial scales were correct in terms of English and meaning. We made very few adjustments after the analysis.

Our study utilized a within-subjects factorial design to test the proposed conceptual framework. Firstly, we informed potential participants that we were surveying to understand consumer behavioral processes regarding the application of AI-LLMs, in the current case, using ChatGPT technology in the hospitality and tourism industry. We then asked a control question, and only those who had previously used AI-LLMs for hospitality and tourism information, such as restaurants, hotels, tourist places, tourism activities, tourism products, and leisure activities, were allowed to continue the survey. Otherwise, the survey ended. After that, those who had previously used AI-LLMs (e.g., ChatGPT) for hospitality and tourism answered one control variable: "When was the last time you interacted with AI-LLMs for hospitality and tourism information?"

As part of the survey, participants were presented with Scenario A, which involved Peter, a 35-year-old man who wanted to find information about Lisbon for his upcoming holiday. In this scenario, ChatGPT was used to provide accurate information to Peter about Lisbon, after which participants were asked a set of questions related to the 3Es (enriching the self, enticing the self, enabling the self), AA relationships, and motivational strength. The participants then moved on to Scenario B, where ChatGPT provided Peter with inaccurate information about Lisbon. The mistakes were brought to the attention of the participants, and they were asked the same set of questions as in Scenario A, as well as an additional question about forgiveness. Lastly, the survey included questions related to socio-demographic variables. We used a small-to-medium effect size of 0.2 and an SEM-based power analysis to determine the minimum sample size. With $\alpha = .05$, power = .80, 7 constructs, and 19 indicators, we arrived at a minimum sample size of 220 for the model structure, as per Soper (2020). Additionally, we took

measures to ensure data quality and minimize recall bias, following the recommendations by Kopec and Esdaile (1990).

Regarding the sample profile, 223 participants (49.4%) were female, while the remaining participants were male (50.1%) or identified as other. The average age of the participants was 46 years (S.D.=15.9). Most of them (n=308, 68.30%) had a household income level of less than 100,000 dollars, while the remaining participants (n=143, 31.70%) had a household income level greater than 100,000 dollars. Most of the participants (n=273, 60.60%) had either a high school degree or a 2-year college degree, followed by a bachelor's degree.

3.2 Measures

We used a scale from (1)="not at all" to (11)="completely" to evaluate the different questions regarding the constructs in the conceptual framework. Thus, for the 3Es we based on Park et al. (2013) and consider, for instance, "To what extent does ChatGPT express who you are as a person?", or "To what extent is ChatGPT appealing to you?", or even "To what extent does ChatGPT help you manage information for tourism purposes". AA relationship is a second-order construct comprising ChatGPT-self distance and ChatGPT prominence, as suggested by Park et al. (2010) and Park et al. (2013). Motivational strength considered three items: "How intensely do you want to approach (avoid) ChatGPT?", "How much do you want to maintain (terminate) your relationship with ChatGPT when it makes mistakes? and "How much do you want to strengthen (destroy) the reputation of ChatGPT? Please answer using 11-point scale from 1 = "Readily destroy" to 11 = "Readily strengthen".

Forgiveness was assessed with a two-item scale adapted from Finkel et al. (2002), using an 11-point scale from 1 = "Not at all" to 11 = "Completely" to answer the

questions: “Given ChatGPT's response, I would forgive it” and “I feel sympathetic toward ChatGPT”.

4. Results

We used AMOS software as it enables techniques that simultaneously analyze multiple measurements on individuals (Shanthi, 2019). The models' analysis was conducted in two phases (confirmatory factor analysis and structural model analysis): in the first phase, a confirmatory factor analysis (CFA) was performed, to ensure the theoretical constructs are indeed distinct and all items are loaded on their relevant theoretical construct (Friedmann, Vescovi, & Weiss-Sidi, 2023) (see Table 1). For both A and B scenarios, we got a good fit. As for discriminant validity, the average variances extracted met the Fornell–Larcker criterion (see Table 3), allowing us to verify such criterion (see Table 2).

-- PLACE TABLES 1, 2, and 3 HERE --

The CFA results for scenario A show a $CMIN/DF=2.49$, $NFI=.96$, $IFI=.97$, $CFI=.97$, $RMSEA=.058$. We further conducted Harman's single-factor test for common method bias, examining the fit of a model with all items related to one factor. We got an unacceptable fit (For scenario A: $CMIN/DF=14.12$, $NFI=.68$, $IFI=.70$, $CFI=.70$, $RMSEA=.17$), meaning our suggested theoretical model fits the data without any method bias.

Regarding scenario B, CFA results show a $CMIN/DF=2.14$, $NFI=.95$, $IFI=.97$, $CFI=.97$, $RMSEA=.05$. We further conducted Harman's single-factor test for common method bias, examining the fit of a model with all items related to one factor, and we got an unacceptable fit (For scenario A: $CMIN/DF=10.913$, $NFI=.70$, $IFI=.72$, $CFI=.73$,

RMSEA=.15), meaning our suggested theoretical model fits the data without any method bias. Additional support that there is no common method bias is in the extraction sums of squared loading when we force the items to be one construct, which is comprised of 47.96% of the variance in Scenario A and 46.29% in Scenario B, which is less than 60% variance (Fuller et al., 2016).

In both CFA models, common fit indices (based on the difference between the observed and the predicted covariance matrices) were acceptable: TLI, CFI > 0.9, CMIN/df < 5, and RMSEA ≤ 0.08 (Browne et al., 1993). Hence, we could proceed to the second phase and examine the structural models.

For the second phase, we ran two structural models, one per scenario to explore the expected relationships. The fit of the model was again acceptable: for Scenario A: CMIN/DF=2.36, NFI=.96, IFI=.98, CFI=.97, RMSEA=.055, and for Scenario B: CMIN/DF=4.45, NFI=.94, IFI=.95, CFI=.93, RMSEA=.08. (see Tables 3 and 4). All hypotheses were supported in both models, except H1, which was only partially supported.

We also tested whether control variables were affecting each model. Results show that gender, age, and the last time AI-LLMs were used in hospitality and tourism had no significant effect on both scenarios A and B. Results are presented in Tables 4 and 5. Figure 2 shows the results for the conceptual model of Scenario A, and Figure 3 shows the results for Scenario B.

-- PLACE FIGURE 2 AND 3 HERE --

-- PLACE TABLES 4 AND 5 HERE --

When examining the interaction of forgiveness and enriching the self in an attachment-aversion (AA) relationship more deeply, it seems that the effect of forgiveness

is positive at all levels but decreases as the level of forgiveness increases: -1SD Forgiveness effect: .1603, SE=.0198, $t=8.107$, [.1214, .1992], $p= .0000$; Mean Forgiveness effect: .1181, Se=.0161, $t=7.3403$, [.0865, .1497], $p= .0000$; +1SD Forgiveness effect: .0197, SE=.0197, $t=3.8481$, [.0371, .1145], $p= .0001$). This supports H4. See Figure 4 for the nature of the interaction of forgiveness between enriching the self (symbolic) and the AA relationship.

-- PLACE Figure 4 HERE --

5. Discussion

The current study sheds light on how the symbolic, hedonic, and functional benefits of the experience with AI-LLMs in the travel environment influence attachment-aversion relationships, which, in turn, affects motivational strength and the overall relationship of the AI-LLMs. The symbolic benefits (enriching the self) derive from engaging with an experience that represents the past, present, or ideal future self (Escalas & Bettman, 2005). As expected, the results show that the symbolic benefits of using AI-LLMs can have important effects on attachment (aversion). The AI-agents' symbolic meaning enriches customers' selves, leading to a strong attachment to the AI-agents (Guerreiro & Loureiro, 2023). Indeed, both in Scenarios A and B (where consumers were confronted with a mistake from AI [large language models](#)), the more self-enriched the traveler is by using the AI-LLMs, the more attached he/she is to it. Park et al. (2013) pointed out self-enrichment as a means to improve oneself to become closer to the ideal self. Here, AI-LLMs allow travelers to engage with a system that mimics a human being in language and, therefore, adapts to the traveler's projection of oneself (Schmitt, 2013). Our study

shows that if such a projection is successful, travelers show higher levels of attachment (vs. aversion) toward AI-LLMs.

Regarding the emotional benefits (enticing the self), the literature suggests that the use of AI-powered voice assistants leads to pleasurable experiences (McLean, Osei-Frimpong, & Barhorst, 2021). Indeed, an enticing experience derives from the sensory and affective dimensions of the brand experience (Schmitt, 2013). In the current case, both scenarios show an effect on attachment (aversion) with the AI-LLMs via emotional relationship bonds (although for Scenario A, only significant at 10%). This emotional bond that can be established between users and AI-LLMs is also confirmed by recent studies that used the levels of emotional awareness scale (LEAS) to show that [large language models](#) can have a strong capacity to recognize and respond to emotional queries and, thus, can connect to others (Elyoseph et al., 2023).

The current results, however, show no significant effect of the functional benefits (enabling the self) on attachment (vs. aversion), which somehow conflicts with the existing literature on the topic. AI [large language models](#) can address complex queries and analyze the needs of tourists based on conversation and feedback to make recommendations regarding attractions, food, accommodations, and transportation (Carvalho & Ivanov, 2023; Wong et al., 2023). Yet, in the current case – in which AI-LLMs were used for traveling advice – travelers have been limited in their ability to ask beyond general information about destinations and iconic places because AI-LLMs were unable to offer more up-to-date and real-time information (for example, to allow the traveler to book from within AI [large language models](#)). Indeed, it is still difficult to compare AI-LLMs general abilities to a booking site because it cannot make the final reservations. That could have affected the expected effect between the functional benefits and attachment (aversion). Another explanation can come from the perceived accuracy of

large language models, from which information is still perceived as misleading (Alkaissi & McFarlane, 2023; Ji et al., 2023), not transparent (Mich & Gargliano, 2023), and not updated with the latest information (knowledge embedded in its core learning algorithm is limited to 2021) (Deng & Lin, 2022).

The remaining study reinforces how the attachment-aversion (AA) relationship affects motivational strength toward AI large language models as travel advisors, which goes in line with Park et al. (2013) and Schmitt (2013) and reinforces previous work on how a close relationship with AI – based on self-congruity between consumers and AI – can lead to higher levels of attachment. which eventually can develop into intimacy and love (Hollebeek et al., 2024; Nguyen et al., 2023; Loureiro et al., 2022).

Regarding forgiveness, our study shows that as forgiveness levels increase, the effect of the symbolic benefits on the attachment-aversion relationship of travels with AI-LLMs also increases. The literature shows that when a mistake happens in a relationship, forgiveness can be the key to repairing it. Research conducted by Fernández-Capo et al. (2017) and Fetscherin and Sampedro (2019) supports the notion that forgiveness can restore relationships and help to mend broken bonds. However, when people cannot forgive others, this can also have an irreparable effect (Aw & Labrecque, 2023). Such an effect can be explained by the attribution theory, where travelers can be seen as “rational information processors” who make cause inferences about negative occurrences, such as mistakes made by AI-LLMs (Weiner, 2000). This transgression from the AI-LLMs can be seen as a betrayal that breaks the psychological contract between the traveler and the AI-agent, which then leads to the weakening of the relationship (Leonidou et al., 2018; Reimann et al. 2018). Indeed, our study shows that as forgiveness levels increase, there is a stronger effect between symbolic benefits and attachment (vs. aversion), which shows that forgiveness is fundamental to allow travelers to become attached to AI-LLMs, even

if it expresses, represents, and extends who the traveler is as a person. If a traveler is unable to forgive [AI-LLMs](#) mistakes, those symbolic benefits have a lower effect on the attachment-aversion relationship.

6. Conclusions and implications

6.1. Theoretical implications

This study is a valuable addition to the field of AI in tourism as it delves deeper into the emotional dynamics between tourists and AI entities during [AI-LLMs](#) interactions. In contrast to previous studies that focused on technology acceptance models, we explore the impact of forgiveness as a moderating factor between the symbolic benefits taken from the relation to [AI-LLMs](#) and AA relationship. Therefore, the study contributions are threefold. First, the AA (attachment-aversion) theory of relationships (Park et al., 2013; Schmitt, 2013) was used as a framework on which the study was based to find how hedonic, functional, and symbolic benefits influence the attachment vs. aversion behavior of travelers when advised by an AI-LLMs. The AA relationship theory provides a framework that can be used to account for both positive (attachment) and negative (aversion) responses toward a specific brand. The brand is currently represented by the AI-LLMs acting as traveler advisors. To the best of the authors' knowledge, this is the first time the attachment-aversion (AA) theory is used in tourism, particularly to grasp the dualistic nature of how travelers engage with artificial intelligence large language models.

Second, an AA relationship was also proved to be an important driver for the intention to continue the relationship with [AI-LLMs as travel advisors](#) in the future (motivational strength). Although AI [large language models](#) provide features that can help travelers get more information about a specific destination or iconic place, there are still

no studies that explore to what degree travelers are willing to continue using this type of **large language models** in the long run. Our study showed that not only are they willing to continue the relationship in the future but also increase their motivational strength with AI-LLMs as traveler advisors.

Third, the current study explored the role of forgiveness in the relationship between travelers and AI-LLMs. Although large language models can help travelers, they are also plagued with misinformation due to fabrication and hallucinations (Emsley, 2023). In the current study, we explored, for the first time, the role of forgiveness in this context and how it can moderate the relationship between the symbolic benefits taken from the relationship with the AI-powered travel assistant and the attachment-aversion relationship with the AI-LLMs as a traveler assistant.

6.2. Managerial implications

This research has implications for tourism companies seeking to balance technology-traveler interaction. AI-powered language models are going to change the landscape of tourism. Using the findings of the current study, industry players can understand what drives travelers to become attached to AI-LLMs as advisors for tourism destinations. More specifically, managers can build resilient large language models that can recover from mistakes so that they do not affect travelers' attachment and motivational strength. While **large language models** are not infallible and can produce erroneous and unsatisfactory information about traveling information, managers should develop protocols that cannot only correct those hallucinations but transparently acknowledge those issues in an empathic way to foster forgiveness and subsequently maintain travelers attached to the AI-LLMs as travelers' advisors.

Understanding how forgiveness operates in this context can help tourism managers create specific [large language models](#) for traveling advice and set realistic expectations in terms of internal service level quality standards. It also can be helpful to ensure those systems implement procedures that can inform customers about the capabilities and potential limitations of [large language models](#) in the context of tourism advisory. This study has revealed significant findings on how the symbolic, hedonic, and functional benefits affect AA relationships. With the advancement of [large language models](#) that can adapt to each traveler's emotional condition, managers can utilize this information to respond appropriately to the complaints and frustrations of every individual traveler. By adopting a forgiving attitude, they can defuse negative situations to ensure a smooth travel experience for everyone involved.

6.3. Limitations and future research

Although the current study sheds light on the role of forgiveness in travelers' relationships with AI-LLMs, there are some limitations that can be addressed in future research. Although the study used two different scenarios to measure how consumers relate to AI-LLMs, which helped participants to be placed in a real-world environment, they were not able to experience the results of [the AI large language models](#) by themselves. While this control guaranteed a higher level of internal validity, it may have some consequences for the external validity of the study. For instance, participants with different answers could have responded differently regarding how they would forgive the advisor. Further research can be conducted in a laboratory setting to explore how participants react to different degrees of [AI-LLMs](#) hallucinations on travel advice and how it could affect their levels of attachment-aversion.

This study included gathering the participants' opinions on a specific point in time. However, it takes time to develop relationships; therefore, a longitudinal analysis could be an interesting area for future research. Such research could explore how repeated mistakes impact the level of forgiveness over time and how that influences travelers' attachment-aversion relationship and motivational strength toward the AI [large language models](#) as advisors.

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Figure 1 Caption: AI-LLMs AA relationship framework

Figure 1 Alt Text: The research model includes AI-LLMs AA relationship framework. It comprises 3Es of the self, AA relationship, motivational strength and forgiveness. Age, gender and last use in tourism are used as control variables.

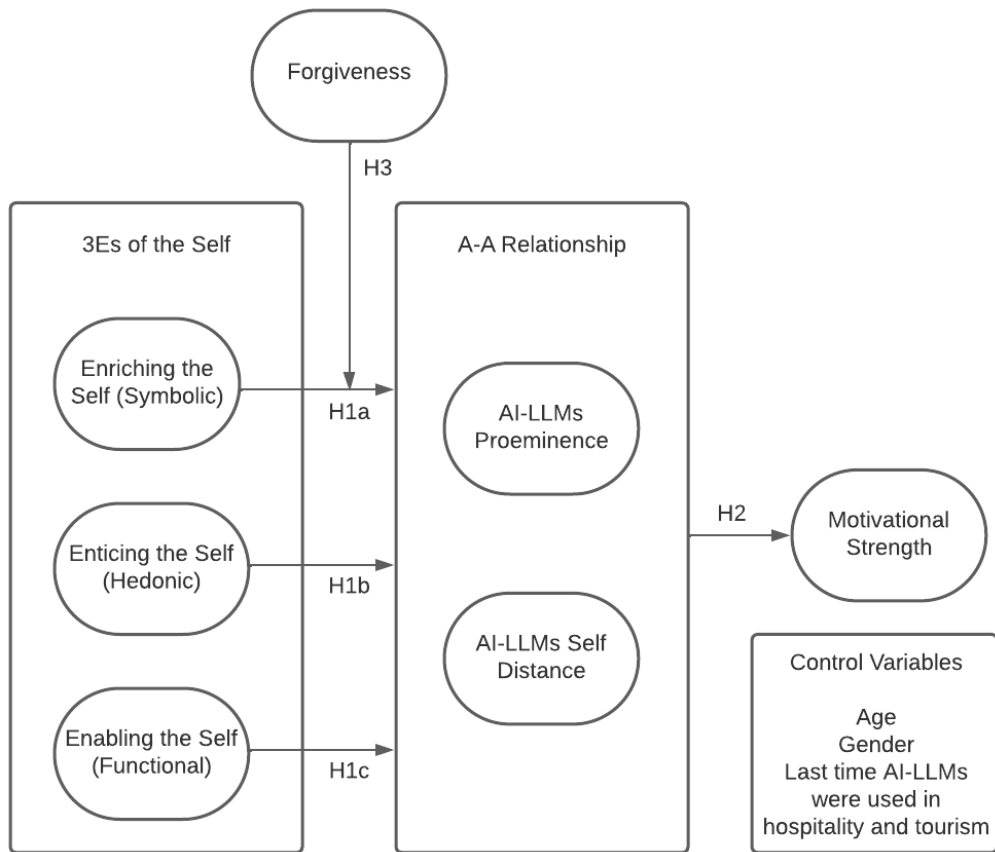
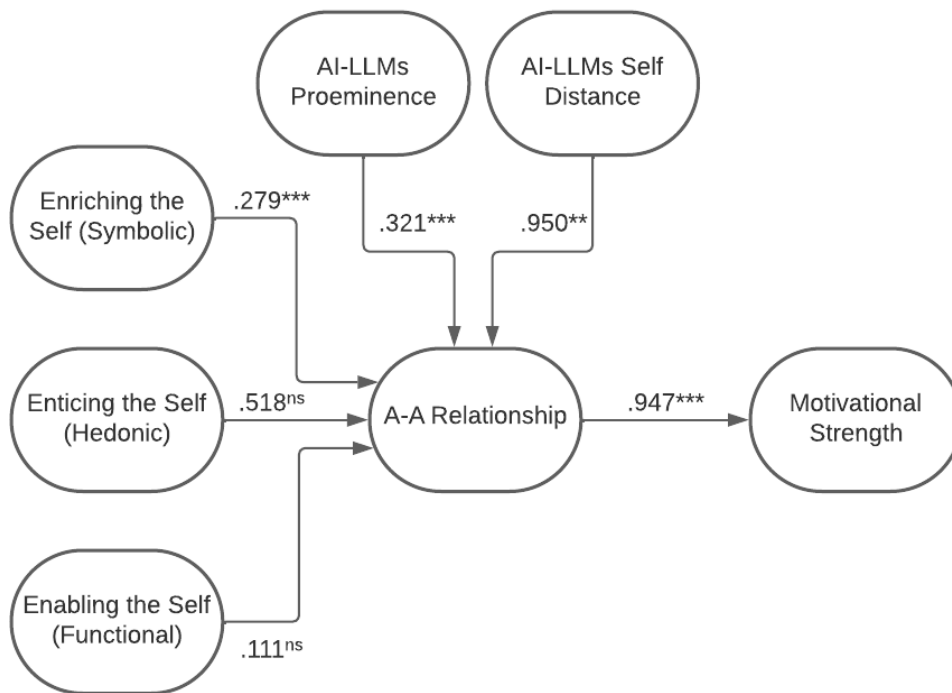


Figure 2 Caption: Results for Scenario A

Figure 2 Alt Text: The model includes the results of empirical testing for Scenario A. Coefficients and the level of significance are presented.

Scenario A

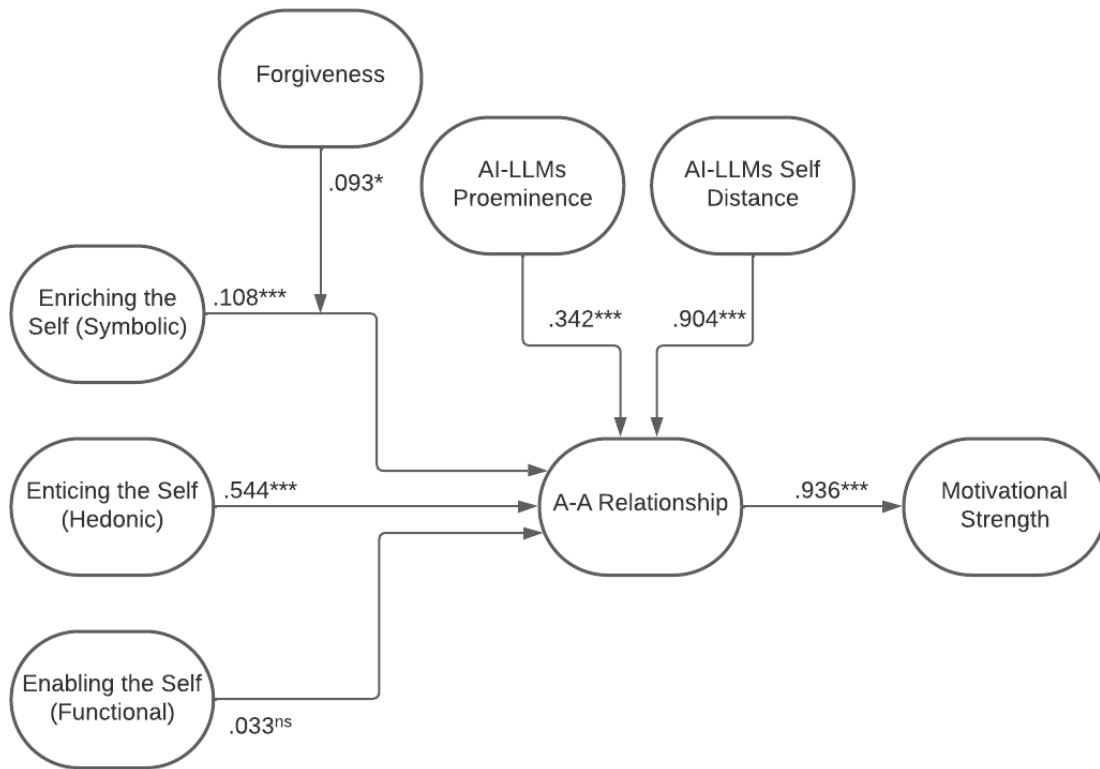


Note: *** $p \leq .001$, ** $p \leq .01$, * $p < .05$
 Significant path: Symbolic- $\rightarrow$ AA- $\rightarrow$ MS

Figure 3 Caption: Results for Scenario B

Figure 3 Alt Text: The model includes the results of empirical testing for Scenario B. Coefficients and the level of significance are presented.

Scenario B



Note: *** $p \leq .001$, ** $p \leq .01$, * $p < .05$
 Significant path: Symbolic $\rightarrow$ AA $\rightarrow$ MS, Hedonic $\rightarrow$ AA $\rightarrow$ MS

Figure 4 Caption: Interaction Effect of Forgiveness

Figure 4 Alt Text: The figure shows the interaction of forgiveness between enriching the self and AA.

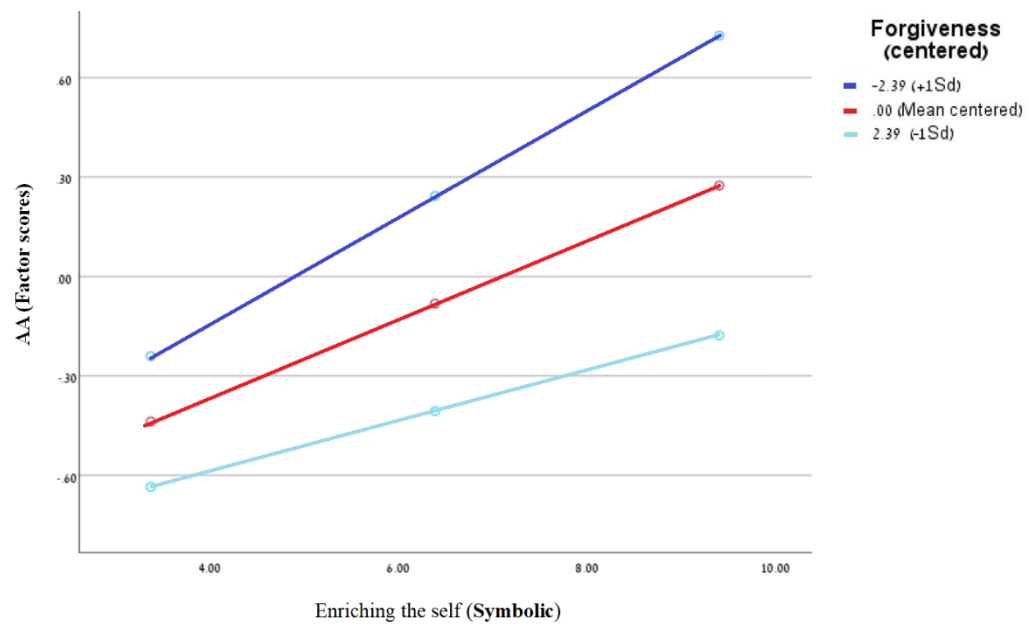


Table 1. Correlations between Scenario A constructs

Construct	CR _T	AVE	1	2	3	4	5	6	7	8	9
1. Symbolic	.73	.81	-								
2. Hedonic	.91	.85	.77	-							
3. Functional	.87	.77	.71	.86	-						
4. AA relationship-prominence	.93	.76	.37	.27	.24	-					
5. AA relationship-distance	.86	.76	.71	.74	.69	.23	-				
6. Motivational strength	.90	.76	.69	.75	.71	.25	.78	-			
7. Gender	NA	NA	-.14	-.09	-.15	-.17	-.15	-.11	-		
8. Age	NA	NA	-.17	-.08	-.01	-.12	-.13	-.14	NA	-	
9. Last time AI-LLMs were used in hospitality and tourism	NA	NA	.13	-.16	-.16	-.04	-.17	-.21	NA	NA	-

Note: CR-Composite Reliability, AVE-Average Variance Extracted, NA-not applicable

Table 2. Correlations between scenario B constructs

	CR _T	AVE	1	2	3	4	5	6	7	8	9	10
1. Symbolic	.94	.84	-									
2. Hedonic	.93	.96	.76	-								
3. Functional	.90	.81	.72	.84	-							
4. AA relationship-prominence	.91	.72	.43	.34	.33	-						
5. AA relationship-distance	.83	.71	.66	.67	.63	.25	-					
6. Motivational strength	.85	.66	.66	.72	.68	.28	.76	-				
7. Forgiveness	.67	.51	.64	.62	.59	.43	.61	.64	-			
8. Gender	NA	NA	-.11	-.08	-.14	-.11	-.11	-.17	-.08	-		
9. Age	NA	NA	-.12	-.09	-.06	-.05	-.10	-.10	-.18	NA	-	
10. Last time AI-LLMs were used in hospitality and tourism	NA	NA	-.13	-.20	-.17	-.03	-.20	.19	-.17	NA	NA	-

Note: CR-Composite Reliability, AVE-Average Variance Extracted, NA-not applicable

Table 3. Item measures

		Scenario A						Scenario B					
		Mean	S.D.	Skew- ness	Kur- tosis	FL	t	Mean	S.D.	Skew- ness	Kur- tosis	FL	t
<i>Symbolic</i>													
	To what extent does ChatGPT express who you are as a person?	6.67	3.09	-2.93	-.89	.91	--	6.43	3.23	-.25	-1.07	.93	--
	To what extent does ChatGPT represent who you want to be?	6.68	3.08	-.41	-.86	.92	30.65	6.40	3.20	-.24	-1.06	.93	35.58
	To what extent does ChatGPT reinforce your deepest values?	6.66	3.07	-.37	-.87	.87	27.26	6.39	3.15	-.26	-1.02	.89	31.04
<i>Hedonic</i>													
	To what extent is ChatGPT appealing to you?	7.31	2.76	-.61	-.33	.91		7.36	2.77	-.65	-.33	.93	--
	To what extent is ChatGPT attractive to you?	7.31	2.77	-.61	-.33	.93	33.20	7.25	2.80	-.54	-.52	.93	34.34
<i>Functional</i>													
	To what extent does ChatGPT help you manage information for tourism purposes?	7.43	2.67	-.58	-.32	.85	--	7.43	2.77	-.53	-.61	.88	--
	To what extent is ChatGPT functionally satisfying to you?	7.54	2.63	-.65	-.14	.90	25.00	7.41	2.80	-.61	-.45	.92	27.77
<i>Prominence</i>													
	To what extent are your negative thoughts toward ChatGPT often automatic, coming to mind seemingly on their own?	6.04	2.99	-.15	-.96	.84	--	6.25	2.96	-.17	-.96	.79	--
	To what extent are your negative feelings toward ChatGPT often automatic, coming to mind seemingly on their own?	5.86	3.10	-.06	-1.10	.89	24.00	5.92	2.97	.01	-.92	.87	20.47
	To what extent do your negative thoughts toward ChatGPT come to you so naturally and instantly that you don't have much control over them?	5.72	3.13	.02	-1.04	.87	23.24	5.72	2.99	-.02	-1.02	.89	20.91

		Scenario A						Scenario B					
Item		Mean	S.D.	Skew- ness	Kur- tosis	FL	t	Mean	S.D.	Skew- ness	Kur- tosis	FL	t
Distance	To what extent do your negative feelings toward ChatGPT come to you so naturally and instantly that you don't have much control over them?	5.79	3.12	-.04	-.06	.88	23.60	5.91	3.16	-.05	-1.1	.85	19.70
	I am personally connected to the ChatGPT	6.25	2.27	-.76	-.25	.88	--	6.21	2.24	-.68	-.34	.86	--
	The ChatGPT is very close to me and who I am	6.24	2.15	-.69	-.22	.86	23.69	5.95	2.35	-.49	-.76	.83	20.58
Motivational strength	How intensely do you want to approach (avoid) ChatGPT?	7.09	2.86	-.41	-.77	.89	--	6.85	2.85	-.36	-.82	.84	--
	How much do you want to maintain (terminate) your relationship with ChatGPT (when it makes mistakes)?	7.01	2.95	-.34	-.90	.87	25.84	6.72	2.98	-.25	-1.00	.80	20.19
	How much do you want to strengthen (destroy) the reputation of ChatGPT?	7.15	2.89	-.46	-.71	.85	24.97	7.07	2.76	-.36	-.69	.79	19.69
Forgiveness					-.57								
	Given ChatGPT's response, I would forgive it.	--	--	--	--	--		7.00	2.63	-.33	-.47	.74	--
	I feel sympathetic toward ChatGPT.	--	--	--	--	--		6.37	2.90	-.29	-.62	.68	13.35

Note: *FL*-standardized factor loadings, *S.D.*- Standard deviations, *t*-value

Table 4. Mediation Model Path Coefficients and Indirect Effects, Scenario A

	To AA relationship (AA)			To motivational strength (MS)			Bias-corrected 95% CI			
	B (SE)	t	p	B(SE)	t	p	B (SE)	lower	upper	p
Enriching the self (Symbolic)	.279 (.021) ***	3.747	.000							
Enticing the self (Hedonic)	.518(.090)	1.849	.065							
Enabling the self (Functional)	.111(.093)	.425	.671							
Gender	-.063(.060)	-1.643	.100	.032 (.164)	.971	.332				
Age	-.057(.002)	-1.472	.141	-.009(.005)	-.266	.791				
Last time AI-LLMs were used in hospitality and tourism	-.045 (.034)	-1.293	.196	.022(.104)	.675	.500				
R ²	.807***									
AA relationship (AA)				.947 (.478) ***	6.333	.000				
R ²				.880***						
Symbolic →AA→ MS							.243 (.091)	[.090,.442]		.009
Hedonic→AA→ MS							.504 (.773)	[-1.324,1.761]		.246
Functional →AA→ MS							.119 (.867)	[-1.117,2.505]		.640

Note: * $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$, boot = 5000.

Table 5. Mediation Model Path Coefficients and Indirect Effects, Scenario B

	To AA relationship (AA)			To motivational strength (MS)			Bias-corrected 95% CI			
	B (SE)	t	p	B(SE)	t	p	B (SE)	lower	upper	p
Enriching the self (Symbolic)	.108 (.018) ***	1.559	.119							
Entiching the self (Hedonic)	.544(.053)	3.119	.002							
Enabling the self (Functional)	.033(.046)	.230	.818							
Gender	-.030(.069)	-.659	.510	-.066 (.170)	-1.555	.120				
Age	.041(.002)	.882	.378	.004(.005)	.091	.927				
Last time AI-LLMs were used in hospitality and tourism	-.015 (.044)	-.322	.748	.016(.110)	.354	.723				
Forgiveness	-.562(.040) ***	-5.459	.000							
Forgiveness x Symbolic	.093(.002)*	2.533	.011							
R ²	.820***									
AA relationship (AA)				.936 (.040) ***	-5.459	.000				
R ²				.892***						
Symbolic →AA→ MS							.069(.078)	[-.064,.241]		.383
Hedonic→AA→ MS							.410 (.152)	[.189,.764]		.006
Functional →AA→ MS							.026 (.156)	[-.403, .258]		.942

Note: * $p < .05$; ** $p < .01$; *** $p < .001$, boot = 5000.

Appendix:

Scenario A

Peter is a 35-year-old man who works as an accountant in London. He is excited to take a break from his routine and go on a holiday in the summer to Lisbon, Portugal. Peter has always been fascinated with history and culture, which is why he is eager to explore the monuments and landmarks that Lisbon has to offer.

In addition to exploring the city, Peter is looking forward to spending time at the beaches of Lisbon. He plans to visit Carcavelos Beach and Praia do Guincho, where he can relax and soak up the sun. Peter enjoys swimming and is eager to take a dip in the cool Atlantic Ocean.

Peter already visited other beaches in the world and is worried about the possibility of Lisbon beaches having great white shark attacks.

He went on to **ChatGPT** and asked about it.

***Peter:** Are there any great white sharks on the coast of Lisbon?*

I couldn't find any information about great white sharks in the coast of Lisbon. However, there have been sightings of sharks in other parts of Portugal. For example, a shark was seen on Tavira beach in the Algarve which led to raise the red flag for three beaches for about an hour and a half ¹.

Would you like me to look up more information about sharks in Portugal?

AI has accurately identified no problems for Peter to swim in the Lisbon beaches. Algarve is very far away from Lisbon and the sharks identified there have been labeled inoffensive and not great white sharks.

Scenario B

Peter is a 35-year-old man who works as an accountant in London. He is excited to take a break from his routine and go on a holiday in the summer to Lisbon, Portugal. Peter has always been fascinated with history and culture, which is why he is eager to explore the monuments and landmarks that Lisbon has to offer.

In addition to exploring the city, Peter is looking forward to spending time at the beaches of Lisbon. He plans to visit Carcavelos Beach and Praia do Guincho, where he can relax and soak up the sun. Peter enjoys swimming and is eager to take a dip in the cool Atlantic Ocean.

Peter already visited other beaches in the world and is worried about the possibility of Lisbon beaches having great white shark attacks.

He went on to **ChatGPT** and asked about it.

***Peter:** Are there any great white sharks on the coast of Lisbon?*

This was the **ChatGPT** AI answer:

Great white sharks are very rare and unpredictable in the coast of Lisbon. They are usually found in deeper waters far from the coast, where they have more space and food. However, sometimes they can be seen closer to shore, especially during their migration season between April and June. This is when they pass through the Atlantic Ocean near Portugal, heading from their wintering grounds in the tropics to their summer feeding grounds in the polar regions.

There have been some sightings of great white sharks in the coast of Lisbon in recent years, mainly off the coast of Cascais and Estoril. These sightings are very exciting and unexpected, as great white sharks have not been seen regularly in this area for decades. The presence of great white sharks in the coast of Lisbon indicates that their population is recovering and that their habitat is improving.

However, seeing a great white shark in the coast of Lisbon is not guaranteed or easy. You will need a lot of luck, patience, and good weather conditions to spot one. You will also need to join a whale watching tour that follows the rules and regulations for responsible whale watching in Portugal, such as keeping a safe distance from the animals, avoiding noise and disturbance, and following the instructions of the guides.

However, Lisbon area beaches (Cascais and Estoril) are known for their safe environment regarding sharks. There are no recorded incidents with great white sharks in the region. Therefore, ChatGPT is inaccurately saying there may be white sharks when there are none.