



Article

How AI-Generated Messages Impact Consumer Behavior in the Tourism Industry

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Abstract

Despite the significant potential of AI applications in tourism marketing communication, consumers' attitudes and behaviors towards the outputs of these applications are still a mystery. To fill this research gap, the current study examines and compares consumer engagement (CE), novelty and attitude perceptions towards tourism destinations and hotel promotional content created by ChatGPT-4o (vs. human) for social media and web pages. According to the results, ChatGPT-generated messages (GPTGMs) play a crucial role on social media compared to human-generated messages (HGMs). Moreover, based on the theory of uses and gratifications (UGT), tourists' perception significantly varies between platforms (social media vs. web pages). This research provides insights for marketers on optimizing message design and selecting effective platforms based on consumer reactions to GPTGMs.

Keywords: generative artificial intelligence; tourism; consumer behavior; source disclosure; content creation

1. Introduction

Marketing communication is at a pivotal point due to generative artificial intelligence (GenAI) technologies, which significantly enhance productivity in areas like sales, content production, and generation processes [1]. Generative Pre-trained Transformer for Chatbots (ChatGPT) is a powerful tool that can deliver personalized and engaging content and is among these technologies. It enhances customer experiences and boosts return on investments, with broad potential in education, healthcare, and finance [2]. In particular, the tourism industry offers significant potential for the use of ChatGPT in planning tourism-related activities by leveraging data on flights, restaurants, locations, and accommodation [3]. In this evolving context, the present study examines how AI-generated messages influence consumer perceptions by comparatively evaluating messages generated by ChatGPT and human experts under different disclosure conditions and on online platforms.

In this study, three related but distinct concepts are used to describe marketing messages based on their production source. The term AI-generated marketing messages (AIGMs) is employed as an umbrella concept referring to all promotional content created using generative AI technologies. Within this category, ChatGPT-generated messages (GPTGMs) specifically denote messages produced by ChatGPT for the purposes of this research. In contrast, human-generated messages (HGMs) refer to content created by human marketing professionals without the involvement of generative AI tools. This conceptual distinction is introduced at the outset to ensure clarity and to facilitate a consistent interpre-



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tation of the analyses and findings presented throughout the study. Accordingly, the study draws on Source Credibility Theory (SCT) and UGT as its primary theoretical frameworks.

ChatGPT can further be employed to create personalized social media messages in marketing communication [4]. Messages that resonate with individual needs can capture attention and boost engagement, leading to a better user experience and a positive brand perception. This process is known as consumer engagement (CE), where consumers actively contribute to the brand content [5]. The role of social media in tourism marketing has been strongly studied recently. Indeed, Ref. [6], in his systematic and empirical literature review, revealed that social media marketing has positive effects on destination image consumer interaction. These findings support the importance of marketing messages produced on digital platforms in the context of tourism on consumer perceptions. CE occurs when consumers interact (liking, commenting, etc.) with brand content. Studies reveal that human-generated content influences CE based on message structure or production processes [7]. Notably, while a growing number of recent studies examined consumer responses to chatbot-generated messages [8], very few have focused on content generated by GenAI tools like ChatGPT [9,10]. In this regard, recent studies reported that the use of AI-generated marketing content may improve CE in online environments [11]. Although consumers respond differently to AI-generated content for various industries [12], more research is needed on how GPTGMs in marketing influence consumer behavior, especially in the tourism industry.

While the earlier literature has mainly examined consumer credibility in the domain of online comments [13], emerging research has turned its attention to how consumers perceive AI-generated messages in marketing settings [10,14]. These studies reveal that the perceived credibility of content may vary between HGMs and GPTGMs. Furthermore, a limited number of studies highlight source credibility as a central factor in shaping consumer behavior [15]. However, the literature lacks sufficient comparative analysis of CE responses to HGMs and GPTGMs in social media marketing for tourism destination campaigns. This limited empirical evidence presents an important research opportunity. To fill this research gap, the current study determines the CE levels of tourism destination messages. Therefore, it focuses on explaining the impacts and adoption of AIGMs on tourism consumers.

This study utilizes two interrelated conceptual models: SCT and UGT. Proposed by [16], SCT posits that consumers' acceptance of advertising depends on the expertise of the advertiser. It explains how individuals assess the trustworthiness and expertise of message sources—human or AI—and how these perceptions influence their credibility perception. SCT has also been used in recent CE research to analyze responses to online message sources [13]. SCT has also been expanded to reveal that consumers' credibility perceptions vary based on whether the content is from AI or a human [10,15]. Consumers may view AIGMs differently than HGMs. Ref. [17] has shown that consumers perceive human and AI-based systems (e.g., ChatGPT) differently. The study states that AI is more effective in sectors where objectivity and accuracy are important, whereas human influencers are more dominant in sectors with high emotional intensity. This finding supports the idea that perceptions of the reliability of AI- and human-generated messages within the scope of SCT can differ depending on the context. Therefore, the credibility of the source is important for understanding CE and attitudes. This research examines CE in tourism with both message types through the lens of SCT, which evaluates the trustworthiness and expertise of message sources.

Additionally, this study uses UGT to show that tourism consumers' motivations and gratifications differ between websites and social media. Proposed by [18], UGT suggests that individuals use different communication channels for various purposes. It is often

applied in consumer behavior studies to explain how people engage with social media for information, entertainment, and socializing [7]. Recent research has explored how consumers' trust in AI-generated messages varies by media choice, building on the SCT and UGT models [19,20]. Accordingly, this study treats SCT and UGT not as explanatory causal models, but as interpretive theoretical frameworks for understanding consumer perceptions of AI and human-generated messages. Therefore, rather than testing causal pathways between variables in this research, these theories guide the interpretation of perceptual differences that emerge under experimentally induced conditions. Moreover, the research endeavors to contribute to theory by adapting and broadening these theories within the emerging context of marketing created by generative AI for the tourism industry. Whereas prior research has largely centered on the content created by human experts, the current work extends these frameworks to examine the credibility of GPTGMs. Through the exploration of message origin, disclosure, and delivery medium, this research not only reaffirms foundational assumptions of SCT and UGT but also contributes to their evolution within the realm of AI-generated content.

Considering the undeniable potential of ChatGPT in content production and its promising place in marketing communication [21], this study provides critical insights for practitioners on optimizing time and cost. Studies examining perceptions towards human- and AI-generated content have focused on online platforms [22]. Accordingly, the current study centers on social media and web pages. Moreover, CE items in the experimental stage were designed by considering the relevant literature [23]. This study also examines consumers' attitude perceptions towards AIGMs and HGMs. As previous studies used various types of content [24] or messages related to hashtags [22], this study examines consumer perceptions of tourism-related messages (destinations and hotels). In the realm of tourism marketing, it also explores consumer reactions to promotional tourism content generated by ChatGPT or human experts.

More precisely, the current research centers on three core consumer response variables: perceived engagement, novelty and attitude. These responses are evaluated under the lens of three contextual conditions: the source of content (AIGM vs. HGM), source disclosure condition and the platform type (social media vs. web pages). Taken together, these factors construct an integrated framework to evaluate the effectiveness of GenAI-driven marketing messages in the tourism industry. The study's primary contribution is not to generalize the impact of AI-generated messages on consumer behavior through explanatory models, but rather to comparatively reveal perceptual patterns that emerge under different sources, explanations, and platform conditions. This approach, despite the descriptive nature of the study's findings, allows for an assessment of the extent to which these theoretical frameworks are meaningful in the context of AI-based marketing communication. Accordingly, this study aims to comparatively reveal perceptual patterns that emerge under experimental conditions. In light of all these theoretical and practical insights, the research questions (RQ) of the current study can be formulated as follows: **(RQ1)** How does source disclosure of GPTGMs affect consumers' perceptions of engagement, novelty and attitude, compared to HGMs? **(RQ2)** How do disclosed GPTGMs affect consumers' perceptions of engagement, novelty and attitude, compared to non-disclosed GPTGMs? **(RQ3)** How do consumers' perceptions of engagement, novelty and attitude toward the messages change across the online platforms (social media and web page)?

Within the scope of this study, the editorial organization is structured as follows. Section 2 describes the theoretical background and provides the detailed literature review to develop the hypothesis. Sections 3 and 4 give the methodological approach and discuss the findings, respectively. Section 5 represents the theoretical and practical implications for the tourism industry. Lastly, future research directions are developed on the pointed limitations.

2. Literature Review

2.1. Source Credibility Theory

SCT, proposed by [16], suggests that a receiver's trust can vary based on the message's source. The perceived credibility of this source is crucial for content adoption and includes three key factors: expertise, which is how capable the source is perceived to be in making accurate assertions; trustworthiness, which reflects how valid the communicator's content is viewed as being [25,26]; and attractiveness, which refers to individuals' perceptions of importance regarding the source of the content [27]. These factors can significantly influence consumers who interact with content from virtual or human marketing experts on online platforms. Furthermore, content strategy is another notable aspect in SCT affecting the consumer's credibility towards the source [26].

The theory also provides a framework used to explain variations in CE [13]. However, the source effects on CE have rarely been examined in the literature [28,29]. Recent studies on SCT have examined how trust perception manifests in GenAI. There are few studies comparing individuals' perceptions of AIGMs and HGMs within this framework. For example, Ref. [24] found that participants perceived AIGMs and HGMs similarly in terms of competence and trustworthiness, regardless of source awareness. However, AIGMs were rated higher for clarity and engagement. Ref. [22] showed that source disclosure can influence preferences.

Another key topic in SCT is whether perceived novelty differs by source. Ref. [30] found that perceived novelty affects how virtual influencers promote tourism. Thus, investigating consumer perceptions of source credibility in tourism could enhance our understanding of consumer behavior and improve brand marketing performance [31].

Source Disclosure, Consumers' Perceived Engagement, Novelty, and Attitude

Brands can motivate consumers to engage with their content, fostering loyalty, satisfaction, trust, and commitment. As online activities increase, consumer communities actively discuss brands, making CE a crucial topic in both industry and academia. CE involves cognitive, emotional, and behavioral dimensions [32] and it can be affected by elements such as the structure, typology and grammar of the content in brand–consumer communication [7]. Moreover, consumer perception towards the source is another noteworthy issue in the CE literature [33]. Consumers' behaviors in content consumption and interaction are influenced by both the content and its source; factors such as the type, structure, and role of the content producer can impact CE. For example, Ref. [34] studied CE levels for luxury brand content on Instagram, highlighting the importance of the content source. Ref. [35] further noted that transparency about the content source affects both brand credibility and CE.

One of the dimensions that may also change depending on the source disclosure is novelty that may arise in the consumer's behavior towards the content. Ref. [36] defines novelty as something entirely new, while relative novelty involves familiar objects in new contexts. Recent studies, such as [37], indicate that AI-generated artworks are often viewed negatively in terms of novelty [22]. Consequently, consumers may react differently to content created by humans versus AI.

The source and its presentation may also influence consumer attitudes, which are closely tied to emotions and mental states. Attitude is defined as a perceived intention to respond positively or negatively to a specific object or group [38]. Research shows a strong connection between attitudes toward online content and the credibility of its source. For instance, Ref. [39] found that perceived source credibility affects attitudes in travelers online. Furthermore, Ref. [40] noted that consumer perceptions of human-generated versus AI-generated luxury advertisements may differ. Based on SCT, the expertise, credibility, and

attractiveness of the content source can influence the attitudes and judgments of content consumers [25,26]. Meanwhile, recent work suggests that consumers' judgments may vary depending on the type of source (human, machine, or virtual application) [22]. SCT posits that individuals' evaluations of a message are shaped by their perceptions of the message's source. However, this study does not aim to test causal relationships between the variables proposed within the framework of SCT; instead, it comparatively examines how consumer perceptions of AI-generated and human-generated messages differ under different source conditions. Accordingly, it investigates whether consumers' perceived levels of interaction, novelty, and attitudes vary depending on the message source. Accordingly, the following hypothesis can be formulated separately for social media and web page platforms:

H_{1a}. *Those who know the source will perceive a significant difference in CE between GPTGMs and HGMs.*

H_{1b}. *Those who know the source will perceive a significant difference in novelty between GPTGMs and HGMs.*

H_{1c}. *Those who know the source will perceive a significant difference in attitude between GPTGMs and HGMs.*

Source disclosure may greatly affect consumers' trust, especially with GPTGMs. In consumer services, personalized marketing and recommendations from GenAI applications can enhance CE [41]. AIGMs can impact consumers' psychological and behavioral responses, prompting recent studies on perceptions of disclosed versus non-disclosed sources of AI content [10]. Ref. [42] found that consumers perceive advertisements differently based on whether they are generated by humans or AI, influenced by agentic and communal appeals. As a result, how consumers view GPTGMs is likely affected by the source disclosure. Clearly stating the source of a message is considered a crucial contextual element that can differentiate how consumers evaluate a message. Moreover, recent experimental studies also show that the impact of AI-generated advertising content on consumer attitudes varies depending on the context, and that source disclosure (AI vs. human) can significantly influence consumer evaluations [43]. The study reported that when source information was disclosed, consumers developed more positive attitudes towards human-generated visuals, and negative evaluations of AI content weakened depending on the motivation for use. These findings support the idea that source disclosure may be a critical boundary condition for consumer perceptions. This study compares perceived levels of interaction, novelty, and attitudes under conditions where the same messages are presented with and without disclosure. This approach aims to reveal how source disclosure creates perceptual differences in consumer evaluations. Thus, this study hypothesizes separately for social media and web pages:

H_{2a}. *Those who read the GPTGMs will perceive a significant difference in CE between disclosure and non-disclosure conditions.*

H_{2b}. *Those who read the GPTGMs will perceive a significant difference in novelty between disclosure and non-disclosure conditions.*

H_{2c}. *Those who read the GPTGMs will perceive a significant difference in attitude between disclosure and non-disclosure conditions.*

2.2. Uses and Gratifications Theory

UGT, introduced by [18], explains why individuals select specific media and their motivations during content consumption. It highlights the relationship between media content and consumers, indicating that attitudes and behaviors can vary across different media types. People use these channels for distinct purposes, like seeking information or entertainment, and express satisfaction through interactions, known as CE [44]. Therefore, popular social media platforms serve different consumer needs. The theory suggests that factors like information-seeking, social interaction, rewards, entertainment, and belonging play a crucial role in shaping media preferences [45].

Consumer Perceptions of AIGMs Across Platforms

As AI applications increasingly generate content on online platforms, their perceived authenticity is crucial for user satisfaction. This shift affects users' motivation and attitudes. Recent research has focused on CE, authenticity, and attitudes toward AIGMs within the UGT framework. For example, Ref. [46] investigated how individuals perceive engagement with virtual celebrities, noting that although they may seem uncanny and unrealistic, AI-generated content can effectively enhance marketing outcomes like brand awareness. Additionally, perceived novelty was identified as a key gratification sought by consumers online, particularly in the context of ChatGPT usage [47]. Moreover, recent studies suggest that users may develop different attitudes toward AIGMs under various circumstances [48].

In summary, individuals use social media and websites for different reasons, and these platforms provide varied gratification based on user needs [49]. Consumer perceptions of GPTGMs in marketing are being examined within the framework of UGT. While most studies reveal the source of AIGMs, few conceal that GenAI is the source. Existing research explores shifts in consumer attitudes toward AIGMs compared to HGMs through UGT, but no study has yet analyzed how perceptions of engagement, novelty, and attitudes toward GPTGMs vary across platforms in the tourism industry. In conclusion, UGT (Universal Technology Theory) suggests that individuals use different media platforms with different expectations and purposes. For example, Ref. [50] explained the adoption of AI-based voice shopping platforms by integrating the technology acceptance model (TAM) and UGT, showing that user attitudes are shaped according to system expectations. This finding supports the idea that evaluations of AI-generated marketing content can vary depending on the platform. In addition, the findings of a comprehensive systematic review and meta-analysis conducted by [6] show that social media-based marketing activities have statistically significant effects on destination perception, travel intention, and the engagement level of tourism consumers. This supports the idea that the type of platform and the message content offered on the platform are critical determinants of consumer responses. This study comparatively examines how AI-generated messages are perceived in social media and web page contexts. Thus, it evaluates whether the same messages presented on different platforms create differences in perceived levels of engagement, novelty, and attitude. Based on the above discussion, the following hypotheses have been proposed:

H_{3a}. *Those who read the undisclosed GPTGMs will perceive a significant difference in CE between message platforms (social media vs. web pages).*

H_{3b}. *Those who read the undisclosed GPTGMs will perceive a significant difference in novelty between message platforms (social media vs. web pages).*

H_{3c}. *Those who read the undisclosed GPTGMs will perceive a significant difference in attitude between message platforms (social media vs. web pages).*

3. Materials and Methods

The methodological approach of this study is based on a comparative examination of differences in consumer perceptions of artificial intelligence and human-generated marketing messages. The research focuses on comparing perceptual evaluations that emerge under experimentally induced conditions. Accordingly, the analysis strategy was determined in line with the comparative and descriptive aim of the study.

3.1. Participants

Surveys were conducted online and face-to-face between August and November 2024. The online surveys were created with Google Forms and shared via WhatsApp and email. To reach as many people as possible throughout Türkiye, the non-probabilistic convenience sampling method [51] was preferred as a sampling technique. Since the total population was unknown, the sample size was determined by considering Equation (1) [52]:

$$n = Z^2 * \frac{pq}{e^2}, \quad (1)$$

where n is the sample size, Z represents the value on Z table at 95% confidence level 1.96, e denotes the error rate (0.05), p is maximum variability at the population. So, the calculation can be performed as follows [53]:

$$n = (1.96)^2 * 0.5 * \frac{1 - 0.5}{0.05} = 384.16, \quad (2)$$

In this respect, the experimental study drew on a total of 390 respondents, which exceeds the sample size of 384. Responses where participants chose not to disclose their demographic information were coded as “prefer not to disclose” in descriptive statistics and stored accordingly. These variables were collected for descriptive purposes only and were not included in experimental analyses. The sociodemographic details of the sample group in different age groups are summarized in Table 1.

Table 1. Descriptives.

Category	Items	N	%
Gender	Male	202	51.79
	Female	188	48.21
Age	18–28	217	55.64
	29–47	137	35.13
	48–59	31	7.95
	60 and older	2	0.51
	Prefer not to disclose	3	0.77
Education	No graduation	1	0.26
	Primary school	2	0.51
	High school	10	2.56
	Bachelor	285	73.08
	Postgraduate	91	23.33
	Prefer not to disclose	1	0.26
Salary	0–10,000	155	39.74
	10,001–20,000	26	6.67
	20,001–50,000	106	27.18
	50,001 and above	95	24.36
	Prefer not to disclose	8	2.05

Turks use online platforms (websites, social media, etc.) more than the global average for brand research, shopping, and searching [54]. According to the Turkish Statistical Institute, over 89% of individuals aged 16–55 in Türkiye engage with online media [55]. This high level of online engagement makes Turkish citizens an appropriate sample group for the study.

3.2. Experimental Design

To assess the impact of source types and disclosure conditions on CE, novelty, and attitude perceptions, promotional content was created by a social media marketing expert and ChatGPT. The focus was on Marmaris and Bodrum, two popular summer tourism destinations in Türkiye [56]. Two social media messages (SMMs) were crafted for Bodrum and a boutique hotel there, while another message promoted Marmaris for a web page. The expert aimed to create short, memorable, and attractive content in Turkish. A similar approach was taken for AI message design. ChatGPT was selected for this study because it is the most widely used language model [57] and is effective in marketing communication [4].

In this study's experimental phase, a between-subjects design was used to examine how the message source (ChatGPT vs. human), source disclosure (disclosed vs. not disclosed), and message platform (social media vs. web page) affect consumers' perceived engagement, novelty, and attitudes. A $2 \times 2 \times 2$ design was employed, and all messages were created in Turkish to maintain consistency in marketing purpose, tone, and style. The experimental design used in this study focuses on observing differences in participants' perceptual evaluations under each condition, rather than modeling causal pathways between independent variables. Accordingly, the analytical approach of this study focuses not on modeling the relationships between engagement, novelty, and attitude variables, but rather on comparatively examining how perception levels regarding these variables change under different experimentally induced conditions. While examining the relationships between variables is suitable for explanatory and causal research designs, the aim of this study is to reveal the differences that artificial intelligence and human-generated messages create in consumer perceptions under different contextual conditions. Therefore, each participant was exposed to only one experimental condition, and evaluations were analyzed through inter-participant comparisons. This approach allows for a clear and straightforward presentation of perceptual differences.

A manipulation check was conducted to assess whether participants correctly perceived the experimental conditions, particularly the source disclosure manipulation. After exposure to the messages, participants were asked to indicate their opinion on who created the content (ChatGPT or a human expert) and whether the message source was explicitly stated. The responses confirmed that participants were able to correctly identify both the message source and the disclosure condition, indicating that the experimental manipulations were successfully applied.

To examine the effects of AIGMs and source credibility on CE, novelty, and attitudes, participants were divided into two groups to evaluate SMMs ($n_{control} = 130$, $n_{treatment} = 130$) and web page ($n_{control} = 65$, $n_{treatment} = 65$) content. Each participant completed questionnaires featuring a theme and two messages from either a human or ChatGPT.

The research design is shown in Figure 1. When sources were concealed due to research constraints, participants were informed about the study's purpose and structure at the end of the survey. Additionally, the validity of the marketing content and scales was confirmed through pre-testing with a small group before data collection.

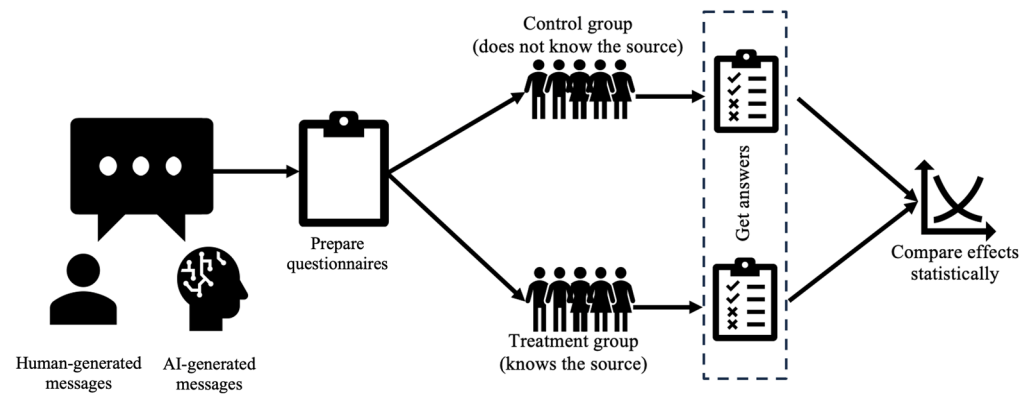


Figure 1. Experimental design.

The experimental procedure involved three steps. First, 130 participants evaluated two social media messages about Bodrum, and a boutique hotel located there without knowing the source. Second, another group of 130 participants evaluated the same messages, but this time the sources were disclosed. Third, 65 respondents assessed web page messages (WPMs) promoting Marmaris, also without knowing the sources, followed by another 65 who were informed of the sources. Participants were randomly assigned to one of four surveys, each representing a combination of platform (social media vs. web page) and disclosure condition (disclosed vs. undisclosed), ensuring a strict between-subjects design for unbiased responses.

3.3. Measures

All scales used in this research were adapted from previous studies. Questionnaire items assessed CE [58–60] and novelty perception [61,62]. Items for perceived attitude were developed from [63]. The scales were translated into Turkish by a tourism expert and verified through back-translation by two marketing experts. A pilot test was conducted with a small group to ensure question clarity before its administration. Based on these measures, respondents were required to express their perceptions on 7-point Likert scales. The last question for determining the attitude perceptions of participants was asked using 7-point judgment with 1 = “very negative” and 7 = “very positive”. All measures are represented in Table 2.

Table 2. Measurement scales used in the study.

Measures ¹	Items	Adapted from
Engagement	I would “like” this post I would comment under this post I would send this post to my friends I would mention my friends under this post	[58–60]
Novelty	This brand post is unique This brand post is different This brand post offers something exciting	[61,62]
Attitude	This post is well made “My general evaluation of this post is. . .”	[63]

¹ All items were translated to Turkish language twice.

The internal consistency of all multi-item constructs was assessed using Cronbach’s alpha coefficients, all of which exceeded the widely accepted threshold of 0.70. Construct validity was examined through confirmatory factor analysis, and it was confirmed that the measurement items loaded satisfactorily with factor loadings to the intended factors.

3.4. Data Analysis and Measurement Validation

In this study, the Mann–Whitney U test, a non-parametric statistical method, was employed using SPSS 30 to test the hypotheses because the assumptions of parametric tests—particularly normality—were not met. However, this choice was not solely driven by assumption violations; it also reflects the comparative aim of the research, which focuses on identifying perceptual differences between independent groups. In this context, the Mann–Whitney U test provides a suitable and robust approach for analyzing distributional differences in consumer perceptions under experimental conditions. Therefore, structural equation modeling and regression-based analyses were not preferred in this study; theoretical frameworks were used as a guide in interpreting the findings.

Although the study’s dataset appears technically suitable for applying methods based on correlation testing, such as regression-based analyses or structural equation modeling (SEM), the applied analysis strategy was deliberately designed to be consistent with the research design. Accordingly, rather than explaining causal/relational mechanisms between variables, the aim was to comparatively reveal perceptual differences between experimentally created independent groups (source type, source disclosure status, and platform type). Therefore, the primary objective of the research is not to model linear relationships between engagement, novelty, and attitude variables, but to test whether consumer evaluations change significantly under different experimental conditions. This approach has made it possible to present simpler, more direct, and interpretable findings, consistent with the research questions.

In the experimental design, the variables tested were engagement, novelty, and attitude perceptions, with participants grouped by message source (ChatGPT vs. human) and source disclosure (disclosed vs. undisclosed). To assess consumer attitudes and perceptions, messages were categorized as social media or web page promotions. The Mann–Whitney U test was utilized instead of the *t*-test due to violations of normality for engagement, novelty, and attitude variables ($p < 0.05$). Effect sizes for all Mann–Whitney U tests were calculated using the $r = Z/\sqrt{N}$ equation and Cohen’s criteria: 0.1 for a small effect, 0.3 for medium, and 0.5 for a large effect [64,65].

The study also conducted a confirmatory factor analysis using SmartPLS 4.1.1.4 to evaluate the internal consistency and validity of the scales. Factor reliability was measured with Cronbach’s α and composite reliability (CR), both exceeding the acceptable threshold of 0.7. As shown in Table 3, convergent validity was confirmed with average variance extracted (AVE) values above 0.5 [66,67]. Furthermore, item loadings were above 0.6 [68], confirming the reliability of all scales.

Table 3. Confirmatory factor analysis results.

Factor	Items	Loadings	CR	AVE	α
Engagement	Liking	0.634	0.869	0.616	0.852
	Commenting	0.760			
	Sharing	0.876			
	Mentioning	0.846			
Novelty	Uniqueness	0.770	0.839	0.634	0.847
	Difference	0.764			
	Excitement	0.853			
Attitude	Structure	0.857	0.787	0.638	0.773
	Evaluation	0.736			

4. Results

The findings are presented in accordance with the comparative and descriptive analytical framework of the study. In this context, the analyses aim to reveal distributional differences in consumer perceptions under different experimental conditions, rather than testing directional or mediating relationships between variables. It examines statistically significant differences in engagement, novelty, and attitudes among independent consumer groups in Türkiye regarding tourist destinations and their evaluations of message sources and disclosures. Therefore, the findings are presented not as a model explaining the relationships between variables, but rather as a comparative report of distributional differences observed between independent experimental and control groups.

4.1. Effect of Message Source (ChatGPT vs. Human) on Tourist Behavior

As can be seen in Table 4, for the disclosed SMMs, results show that commenting ($U = 6630$, $p < 0.05$, $r = -0.16$), sharing ($U = 6636.5$, $p < 0.05$, $r = -0.16$), and mentioning ($U = 6830.5$, $p < 0.05$, $r = -0.13$) perception scores are significantly dissimilar between source types (ChatGPT vs. human) with a low effect size. However, consumer liking behavior does not exhibit statistically significant distinction between the source types ($p > 0.05$). Moreover, when examining the group means, GPTGMs received higher scores from Turkish tourism consumers than HGMs. Accordingly, the data partly supports the first hypothesis (H_{1a}) for social media, indicating that some of the hypotheses regarding the items under a factor are supported. This finding is in accordance with previous studies [34,35].

Table 4. The difference in the distributions of tourist behavior scores between source types for disclosed messages.

Platform	Behavior	Message Source	Disclosure					
			N	Mean	U	p^1	Z	r
Social media ²	Liking	ChatGPT	127	135.81	7009	0.063	−1.682	−0.11
		Human	127	119.19				
	Commenting	ChatGPT	127	138.80	6630	0.013	−2.490	−0.16
		Human	127	116.20				
	Sharing	ChatGPT	127	138.74	6636.5	0.013	−2.475	−0.16
		Human	127	116.26				
	Mentioning	ChatGPT	127	137.22	6830.5	0.032	−2.148	−0.13
		Human	127	117.78				
	Uniqueness	ChatGPT	127	134.10	7226.5	0.147	−1.448	−0.09
		Human	127	120.90				
	Novelty	ChatGPT	127	141.22	6322.5	0.003	−3.014	−0.19
		Human	127	113.78				
	Excitement	ChatGPT	127	147.32	5547	<0.001	−4.358	−0.27
		Human	127	107.68				
	Attitude	ChatGPT	127	150.30	5169.5	<0.001	−5.030	−0.31
		Human	127	104.70				
	Evaluation	ChatGPT	127	148.11	5447.5	<0.001	−4.546	−0.28
		Human	127	106.89				

Table 4. Cont.

Platform	Behavior	Message Source	Disclosure					
			N	Mean	U	p^1	Z	r
Web ³	CE	Liking	64	59.30	1715.5	0.068	−1.825	−0.16
			65	70.61				
		Commenting	64	65.70	2035	0.828	−0.217	−0.02
			65	64.31				
		Sharing	64	61.11	1831	0.234	−1.191	−0.10
			65	68.83				
		Mentioning	64	63.82	2004.5	0.718	−0.361	−0.03
			65	66.16				
	Novelty	Uniqueness	64	54.41	1402	0.001	−3.236	−0.28
			65	75.43				
		Difference	64	60.09	1766	0.134	−1.499	−0.13
			65	69.83				
	Attitude	Excitement	64	61.74	1871.5	0.317	−1.001	−0.09
			65	68.21				
		Structure	64	64.58	2053	0.897	−0.130	−0.01
			65	65.42				
		Evaluation	64	64.31	2036	0.831	−0.213	−0.02
			65	65.68				

¹ Two-sided p -value. ² H_{1a} : Liking = not supported; commenting = supported; sharing = supported; mentioning = supported. H_{1b} : Uniqueness = not supported; difference = supported; excitement = supported. H_{1c} : Structure = supported; evaluation = supported. Overall, H_{1c} is supported; H_{1a} and H_{1b} are partly supported for the SMMs. ³ H_{1a} : Liking = not supported; commenting = not supported; sharing = not supported; mentioning = not supported. H_{1b} : Uniqueness = supported; difference = not supported; excitement = not supported. H_{1c} : Structure = not supported; evaluation = not supported. Overall, H_{1a} and H_{1c} is not supported, and H_{1b} is partly supported for the WPMs. (GPTGMs = ChatGPT-generated messages; HGMs = human-generated messages; SMMs = social media messages; WPMs = web page messages).

For disclosed WPMs, the analysis did not yield a significant dissimilarity between source types ($p > 0.05$). This does not support consumer tendencies for greater CE behavior in GPTGMs or HGMs. However, H_{1a} was not supported for web pages as no statistically significant difference in CE was observed between groups ($p_{liking} = 0.068$, $p_{commenting} = 0.828$, $p_{sharing} = 0.234$, $p_{mentioning} = 0.718$).

The findings revealed a statistically significant divergence between two groups in terms of message difference ($U = 6322.5$, $p < 0.05$, $r = -0.19$), and excitement ($U = 5547$, $p < 0.05$, $r = -0.27$) with a small effect size in SMMs.

Disclosed GPTGMs demonstrated higher mean ranks ($M_{difference} = 141.22$, $M_{excitement} = 147.32$) compared to disclosed HGMs ($M_{difference} = 113.78$, $M_{excitement} = 107.68$) in social media, suggesting GPTGMs were perceived as more novel. Looking at web page messages, consumers perceived HGMs as more unique ($M_{uniqueness} = 75.43$) compared to the GPTGMs ($M_{uniqueness} = 54.41$) at a statistically significant level ($p < 0.05$). The results showed that consumer perceptions of novelty significantly changed between disclosed GPTGMs and HGMs, partly validating H_{1b} for designed SMMs and WPMs. Although past studies have found that individuals may be prejudiced against content if they know that the content producer is AI [22–37], the hypothesis of the current study does not support this situation.

Considering tourists' attitudes toward SMMs, GPTGMs achieved a higher mean rank both for perceived message structure ($M = 150.30$, $U = 5169.5$, $p < 0.05$, $r = -0.31$) and evaluation ($M = 148.11$, $U = 5447.5$, $p < 0.05$, $r = -0.28$) than HGMs with medium effect sizes. Thus, these findings confirm H_{1c} that consumer attitudes for the disclosed SMMs vary between GPTGMs and HGMs. These results support the findings of previous studies [39,40] while providing insights into the understanding of the SCT framework [25]. On the other

hand, the current study found no statistically significant dissimilarity between two groups for WPMs ($p > 0.05$). So, these findings fail to provide evidence for the hypothesis H_{1c} for web pages.

4.2. Effect of Message Disclosure (vs. Non-Disclosure) on Tourist Behavior

As summarized in Table 5, the CE scores of consumers do not significantly differ between disclosed (vs. non-disclosed) GPTGMs ($p > 0.05$) on social media. This indicates that the source disclosure was perceived to be less critical. Also, web messages show diverse consumer sharing ($U = 1635$, $p < 0.05$, $r = -0.18$) behavior with a small effect size regarding CE. In this sense, non-disclosed messages achieved a higher mean rank ($M_{sharing} = 70.95$) than disclosed messages ($M_{sharing} = 58.05$). These findings provide evidence that H_{2a} is partly supported only for WPMs, and this is in line with the past research [42]. However, this hypothesis is rejected for SMMs ($p > 0.05$).

The experimental test findings also revealed that there is no statistically significant difference between disclosed and non-disclosed conditions in terms of the novelty and attitude perception of Turkish tourists for SMMs prepared by ChatGPT ($p > 0.05$). This suggests that even if the source of the message was disclosed to consumers, this did not significantly change their tendencies toward GPTGMs or HGMS. However, the disclosure status of the GPTGM designed for web pages caused consumer judgments to differ based solely on perceived uniqueness ($U = 1400$, $p < 0.05$, $r = -0.28$) and difference ($U = 1566$, $p < 0.05$, $r = -0.21$) with small effect sizes. In this sense, non-disclosed GPTGMs exhibited higher mean ranks ($WPM_{uniqueness} = 74.63$, $WPM_{difference} = 72.03$) compared to disclosed messages ($WPM_{uniqueness} = 54.38$, $WPM_{difference} = 56.97$), pointing to a trend of higher ratings among consumers. In conclusion, H_{2b} was partly supported for web page messages, but not for social media messages.

Table 5. The difference in the distributions of tourist behavior scores between disclosure conditions for GPTGMs.

Platform	Factor	Behavior	Disclosure	ChatGPT					
				N	Mean	U	p^1	Z	r
Social media ²	CE	Liking	Disclosure	127	128.74	8222.5	0.955	−0.057	0.00
			Non-disclosure	130	129.25				
		Commenting	Disclosure	127	126.36	7919.5	0.568	−0.571	−0.04
			Non-disclosure	130	131.58				
		Sharing	Disclosure	127	126.75	7969	0.626	−0.487	−0.03
			Non-disclosure	130	131.20				
		Mentioning	Disclosure	127	128.27	8162.5	0.875	−0.158	−0.01
			Non-disclosure	130	129.71				
	Novelty	Uniqueness	Disclosure	127	122.59	7441.5	0.167	−1.382	−0.09
			Non-disclosure	130	135.26				
		Difference	Disclosure	127	128.19	8151.5	0.860	−0.176	−0.01
			Non-disclosure	130	129.80				
	Attitude	Excitement	Disclosure	127	129.36	8209.5	0.938	−0.078	0.00
			Non-disclosure	130	128.65				
		Structure	Disclosure	127	131.48	7939.5	0.587	−0.543	−0.03
			Non-disclosure	130	126.57				
		Evaluation	Disclosure	127	128.84	8235	0.973	−0.034	0.00
			Non-disclosure	130	129.15				

Table 5. Cont.

Platform	Factor	Behavior	Disclosure	ChatGPT					
				N	Mean	U	p^1	Z	r
Web ³	CE	Liking	Disclosure	64	61.14	1833	0.288	−1.064	−0.09
			Non-disclosure	64	67.86				
		Commenting	Disclosure	64	59.05	1699	0.091	−1.689	−0.15
			Non-disclosure	64	69.95				
		Sharing	Disclosure	64	58.05	1635	0.046	−1.998	−0.18
			Non-disclosure	64	70.95				
		Mentioning	Disclosure	64	60.93	1819.5	0.269	−1.105	−0.10
			Non-disclosure	64	68.07				
	Novelty	Uniqueness	Disclosure	64	54.38	1400	0.002	−3.129	−0.28
			Non-disclosure	64	74.63				
		Difference	Disclosure	64	56.97	1566	0.020	−2.330	−0.21
			Non-disclosure	64	72.03				
	Attitude	Excitement	Disclosure	64	58.91	1690.5	0.081	−1.745	−0.15
			Non-disclosure	64	70.09				
		Structure	Disclosure	64	59.72	1742	0.134	−1.500	−0.13
			Non-disclosure	64	69.28				
		Evaluation	Disclosure	64	57.47	1598	0.027	−2.213	−0.20
			Non-disclosure	64	71.53				

¹ Two-sided p -value. ² H_{2a}: Liking = not supported; commenting = not supported; sharing = not supported; mentioning = not supported. H_{2b}: Uniqueness = not supported; difference = not supported; excitement = not supported. H_{2c}: Structure = not supported; evaluation = not supported. Overall, H_{2a}, H_{2b} and H_{2c} are not supported for the SMMs. ³ H_{2a}: Liking = not supported; commenting = not supported; sharing = supported; mentioning = not supported. H_{2b}: Uniqueness = supported; difference = supported; excitement = not supported. H_{2c} is not supported for the SMMs. H_{2c}: Structure = not supported; evaluation = supported. Overall, H_{2a}, H_{2b}, and H_{2c} are partly supported for the WPMs. (GPTGMs = ChatGPT-generated messages; HGMs = human-generated messages; SMMs = social media messages; WPMs = web page messages).

Moreover, consumers' general evaluation scores for the WPMs significantly differ according to the source disclosure condition, indicating that consumers' evaluation of WPMs increase when the message was masked. Thus, the findings provide partial evidence for the web page scenario of H_{2c}. This finding supports recent work indicating that consumer behavioral perception can be affected by the disclosure condition of AI [10,42]. However, no statistically significant dissimilarity in tourists' attitudes was detected for SMMs ($p > 0.05$).

4.3. Effect of Message Platform (Social Media vs. Web Page) on Consumer Behavior Toward GPTGMs

To determine whether consumers' perceptions towards GPTGMs vary according to the platform from the UGT perspective, messages promoting the cities of Marmaris and Bodrum were used. Moreover, the source of GPTGMs was also hidden to avoid participants' bias at this stage. As shown in Table 6, consumer liking in CE behavior differs significantly ($U = 1671, p < 0.05$) between message platforms.

Considering message novelty, the findings indicated a significant divergence in perceived message uniqueness ($U = 1604.5, p < 0.05$) and difference ($U = 1666.5, p < 0.05$) between the two groups. The analysis also validates that consumers' perception of message structure scores ($U = 1647.5, p < 0.05$) for GPTGMs differ significantly between social media and web pages. Moreover, the mean ranks indicate that web page messages achieved higher scores relative to social media messages, suggesting a likely increase in consumer ratings exposed to web page messages prepared by ChatGPT.

Table 6. The difference in the distributions of item scores between GPTGM platforms (social media vs. web page).

Consumer Perception		Platform	N	Mean	U	p^1	Z	r
Engagement ²	Liking	Social media	65	58.71	1671	0.047	−1.986	−0.17
		Web page	64	71.39				
	Commenting	Social media	65	59.82	1743.5	0.109	−1.605	−0.14
		Web page	64	70.26				
	Sharing	Social media	65	59.71	1736	0.101	−1.641	−0.14
Web page		64	70.38					
Novelty ³	Mentioning	Social media	65	58.87	1681.5	0.057	−1.902	−0.17
		Web page	64	71.23				
	Uniqueness	Social media	65	57.68	1604.5	0.023	−2.269	−0.20
		Web page	64	72.43				
	Difference	Social media	65	58.64	1666.5	0.048	−1.973	−0.17
Web page		64	71.46					
Attitude ⁴	Excitement	Social media	65	61.67	1863.5	0.295	−1.047	−0.09
		Web page	64	68.38				
	Structure	Social media	65	58.35	1647.5	0.037	−2.085	−0.18
		Web page	64	71.76				
	Evaluation	Social media	65	58.92	1685	0.056	−1.907	−0.17
Web page		64	71.17					

¹ Two-sided p -value. ² H_{3a} : Liking = supported; commenting = not supported; sharing = not supported; mentioning = not supported. Overall, H_{3a} is partly supported. ³ H_{3b} : Uniqueness = supported; difference = supported; excitement = not supported. Overall, H_{3b} is partly supported. ⁴ H_{3c} : Structure = supported; evaluation = not supported. Overall, H_{3c} is partly supported. (GPTGMs = ChatGPT-generated messages; HGMs = human-generated messages; SMMs = social media messages; WPMs = web page messages).

These results support UGT, which is based on the principle that individuals can use different media platforms with different motivations [18,49] and is also consistent with past studies that revealed differences in attitudes toward GenAI [48].

In summary, the accepted hypotheses in this research include statistically reliable findings. However, the effect sizes calculated at low-to-medium levels indicate that the explained variance may be relatively low. This may not indicate a major change in consumer perceptions or attitudes. On the other hand, one probable explanation for this situation could be that GenAI technology is still relatively new to society. Thus, limited familiarity, established norms, and possible subconscious biases around GenAI may reduce the magnitude of its impact on consumer evaluations.

These results are meaningful for explaining tourist behavior toward early GenAI technologies in the real world. Within the perspective of the research aim, the overall support or rejection of each hypothesis is briefly summarized in Tables 7 and 8 to provide a cohesive view of the study's findings.

Table 7. Hypothesis results for the source credibility theory.

Hypotheses (SCT)	Social Media	Web Page	Explanation
H_{1a}	Partly supported	Not supported	On social media, disclosed GPTGMs scored significantly higher than disclosed HGMs for commenting, sharing, and mentioning behavior of consumers ($p < 0.05$).
H_{1b}	Partly supported	Partly supported	Disclosed GPTGMs on social media were perceived as significantly more different and exciting than disclosed HGMs ($p < 0.05$). HGMs on the web page were perceived as significantly more unique than GPTGMs ($p < 0.05$).

Table 7. Cont.

Hypotheses (SCT)	Social Media	Web Page	Explanation
H _{1c}	Supported	Not supported	On social media, disclosed GPTGMs scored significantly higher than HGMs for structure and general evaluation of the content ($p < 0.05$).
H _{2a}	Not supported	Partly supported	On web pages, undisclosed GPTGMs received significantly higher scores only in sharing behavior than those with disclosed sources ($p < 0.05$).
H _{2b}	Not supported	Partly supported	On web pages, undisclosed GPTGMs were significantly perceived as more unique and different than those with disclosed sources ($p < 0.05$).
H _{2c}	Not supported	Partly supported	On web pages, undisclosed GPTGMs got a better evaluation than those with disclosed sources ($p < 0.05$).

(GPTGMs = ChatGPT-generated messages; HGMs = human-generated messages).

Table 8. Hypothesis results for the uses and gratification theory.

Hypotheses (UGT)	Result	Explanation
H _{3a}	Partly supported	Undisclosed GPTGMs received significantly more like scores on the web page than on social media ($p < 0.05$). However, there is no significant change on other CE scores ($p > 0.05$).
H _{3b}	Partly supported	Undisclosed GPTGMs were perceived as significantly more unique and different on the web page than on social media ($p < 0.05$). However, there is no significant change on other novelty scores ($p > 0.05$).
H _{3c}	Partly supported	Undisclosed GPTGMs were perceived as significantly more structured ($p < 0.05$). However, there is no significant change on other attitude scores ($p > 0.05$).

(GPTGMs = ChatGPT-generated messages).

5. Conclusions

The findings of the current study comparatively reveal perceptual differences that arise under different contextual conditions rather than establishing causal relationships to explain the effects of AI-generated marketing messages on consumer perceptions. In this respect, the study adopts an experimental and interpretive approach that evaluates the extent to which these theoretical frameworks of SCT and UGT offer explanatory guidance in the context of AI-based marketing communication, rather than directly testing causal relationships among variables. Accordingly, the results of this research should be interpreted within the boundaries of this comparative analytical framework. Therefore, instead of testing theoretical frameworks as explanatory causal models, this study offers a comparative approach that evaluates the explanatory power of these frameworks in interpreting perceptual differences observed under experimental conditions.

The existing literature highlights the impact of source disclosure and media types on consumer behavior, yet there is a significant research gap regarding tourist perceptions and their connection to AIGMs. This study addresses this gap by examining key elements—GPTGMs (vs. HGMs), source disclosure (vs. non-disclosure), and message platform—within the context of consumer behavior. Using a diverse dataset, the findings offer valuable insights that enhance both theoretical frameworks and practical applications related to GenAI technology in tourism marketing.

5.1. Theoretical Implications

Through in-depth analysis of key constructs relevant to consumer perceptions of GPTGMs, this study significantly enhances theoretical knowledge in the field by embedding the findings into SCT and UGT.

This study firstly contributes to understanding how the source of content and its disclosure impact consumer behavior in the Turkish tourism industry. According to SCT, the expertise of the content source influences consumer perceptions [25,26]. Recent research shows that consumer perceptions differ between AIGMs and HGMs [42]. The findings of this study indicate that, despite source disclosure, GPTGMs for social media are viewed as more engaging than HGMs. These results are consistent with the view highlighted by [17] that “AI is perceived as more unbiased and rational across different product categories.” Therefore, the more positive evaluation of ChatGPT content in the context of social media can be explained by consumers interpreting the content source through expertise and objectivity. Additionally, HGMs for web pages are perceived as more unique, suggesting that consumers assess social media and web page content differently. Consumer behavior towards GPTGMs and HGMs remains consistent on web pages, suggesting that in hedonic environments, message content may be more influential than source disclosure. While this contrasts with some previous studies [22,37], this research highlights the significance of source type and the platform’s hedonistic gratifications.

The second contribution to theory examines how consumer perceptions of GPTGMs vary based on source disclosure. The findings demonstrate that the concept of source credibility, as proposed within the framework of SCT, operates in a context-sensitive manner when dealing with messages generated by artificial intelligence. This study reveals that whether the source is AI or human is not the sole determining factor; rather, it creates significant differences in consumer perceptions when considered together with the platform on which the message is presented and the way the source is disclosed. Therefore, rather than being validated as a causal model in this study, SCT offers an expanded interpretive framework to explain how consumers evaluate AI-based content. According to Lasswell’s communication theory [69], the message source significantly influences evaluation. Previous studies indicate that consumers assess messages based on the match between the source and context [70]. In experiments based on SCT, consumer behavior toward GPTGMs in social media did not significantly change with source disclosure. However, when ChatGPT is acknowledged as the source, there is a decline in consumer sharing, evaluation, and novelty scores. This cautious response contrasts with the more heuristic nature of social media, suggesting that disclosing ChatGPT may induce skepticism or reduce perceived credibility. These results, consistent with [43], show that consumer attitudes toward AI content may differ depending on the source disclosure. Therefore, disclosure of the ChatGPT source can create a more cautious evaluation process in consumers, especially on platforms where more functional evaluations are made.

Lastly, the study shows that consumers’ perceptions differ between social media and web pages. According to UGT, individuals select channels to meet specific needs [44]. This framework also applies to how consumers perceive content from ChatGPT [47]. Findings obtained within the framework of UGT show that consumers evaluate AI-generated messages with different expectations on different platforms. While interaction and entertainment-focused perceptions come to the forefront in social media environments, structure, organization, and information quality become more decisive on web pages [44,45]. These results reveal that the platform-based satisfaction differences predicted by UGT are also valid in the context of AI-generated marketing content. Factors like perceived engagement and novelty influence consumer satisfaction with online channels. Ultimately, the study emphasizes the significant role of channel type—social media versus web pages—on consumer behavior in tourism-related AIGMs, enhancing our understanding of UGT.

The fact that disclosing the source, especially in the context of a website, alters consumer perceptions indicates that the dimensions of trust and expertise envisioned by SCT are activated differently depending on the platform. This finding suggests that transparency

in AI-generated content does not produce the same perceptual result in every context; on the contrary, consumers tend to make more cautious assessments in environments where information is presented in a more functional and detail-oriented manner. This indicates that SCT needs to be re-evaluated in the context of AI.

In short, the current study extends SCT by demonstrating how source credibility depends on content novelty and how perceptions of expertise vary across platforms and disclosure conditions. Furthermore, it applies UGT to the context of AI marketing, demonstrating how platform-specific gratifications shape consumer responses.

Although the findings of this study do not establish causal relationships, the comparative evidence provided offers crucial insights into how established communication theories can be reinterpreted in the context of generative AI.

5.2. Practical Implications

The findings of this study offer important insights for tourism marketing professionals using generative AI tools like ChatGPT in their communication strategies. ChatGPT can enhance content production productivity [1]. Consumers view tourism-related content generated by ChatGPT on social media as interactive, unique, and well-structured. Thus, this study guides tourism practitioners in using ChatGPT to create engaging content that appeals to consumers' desires for hedonistic gratification on social media.

Second, the current study identifies differences in consumers' attitudes and evaluations towards AIGMs depending on the source disclosure. Positive emotions and trust in the source play a significant role in how consumers engage with the content [16,29]. Findings indicate that consumers are more cautious and value human sources on web pages. As detailed information becomes more common online, marketers must consider the implications of source disclosure on perceived novelty and attitudes. This insight can help tourism companies adjust their messaging—using concise content for social media and detailed information for websites—while managing AI source transparency.

Ultimately, this study compares social media and web page channels as platforms showcasing tourism-related ChatGPT content based on consumer viewpoints. Although brands share content about their products and services through many channels, comprehending the motivations behind consumers' use of these channels is crucial in obtaining positive feedback across different behavioral contexts, especially CE [44,45]. This research postulates that the perceptions of participants who are consuming touristic AIGMs through social media and web page differ. It confirmed that web pages including touristic destination content prepared by ChatGPT can improve the consumers' evaluations, commenting, and difference perceptions. In line with UGT, the results highlight participants' diverse perceptions of online platforms. Therefore, when tourism marketing practitioners collaborate with AI in content creation, the recommendations of the current study will be useful in understanding which media channels are followed by consumers for which desires, needs and purposes.

5.3. Limitations and Future Scope

While the current study advances our body of knowledge of AIGMs in social media and web pages by examining the effect of ChatGPT (vs. human) generated messages and source disclosure (vs. non-disclosure) on consumer perceptions, future research is necessary to address certain limitations and build upon its insights. First, the analyses primarily focus on comparing perceptual differences between experimental conditions; they do not model causal relationships or mediating and regulatory mechanisms between fundamental constructs such as engagement, novelty, and attitude. Therefore, inferences about how message source and its disclosure influence consumer responses, and through

what processes and under what conditions, remain limited. Hence, future studies could utilize advanced statistical methods such as regression-based models, mediating and moderating effect analyses, or SEM to delve deeper into the relationships between the variables comparatively examined in this research. Specifically, the mediating role of variables such as perceived trust, expertise, transparency, or content utility and the moderating effects of factors such as platform type or user experience could be investigated to more comprehensively test the theoretical mechanisms predicted by SCT and UGT in the context of AI-generated marketing content. Additionally, supporting experimental designs with longitudinal data collection strategies will provide valuable contributions to examining how the effects of AI-generated marketing messages on consumer perceptions change over time.

Furthermore, the study relies on a non-probabilistic convenience sampling method, which limits the generalizability of the findings beyond the experimental context. Accordingly, the results should be interpreted with caution, as they reflect the perceptions of the specific sample studied, not the broader population. Future research using probabilistic sampling strategies or diverse participant pools will enhance the external validity of findings related to AI-generated marketing communication.

Third, this study focused on the Turkish tourism industry. Since the study was not designed to test culture-specific or cross-cultural theoretical propositions, cultural dimensions were intentionally omitted from the hypothesis-building process. Instead, Türkiye was treated as a single, stable empirical context to minimize cultural variance and allow for a clearer comparison of message source, disclosure, and platform effects. However, in an increasingly globalized world, gaining knowledge about other cultures is vital for intercultural communication and helps promote genuine dialog in the tourism industry [71]. Accordingly, upcoming research should shift its focus to different countries' tourism activities. Fourth, two popular destinations (Bodrum and Marmaris) and a boutique hotel were promoted as themes in the messages to be evaluated by consumers. Previous studies considered ChatGPT as a useful tool for hotel reviews, email composition or policy information in tourism communication [72]. Thus, further research should explore various topics. Moreover, since the sample size obtained for WPMs ($n \approx 65$ for each group) may have imposed limitations on statistical effect levels, the use of larger sample sizes for similar scenarios in future studies will expand the literature and may lead to more meaningful results. Finally, this study examined the effect of AIGMs and its disclosure on consumers' engagement, novelty, and attitude perceptions in the case of ChatGPT. However, various factors such as content type, creativity, and brand personality in the content that is prepared by ChatGPT may affect consumer behavior [40]. Therefore, future studies should investigate different AIGMs on consumer preferences.

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