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Research Article

Generative AI-Driven Personalised Content and Its Impact on Consumer Engagement in Destination Marketing in the UK: The Moderating Role of Normative Influence

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Abstract:

Introduction: The research examined the effect of AI on content personalisation and increasing engagement in destination marketing with the moderating effect of normative influence.

Methods: The quantitative analysis was applied and the data obtained through an online, structured questionnaire with five-point Likert scale on 356 individuals residing in the UK. The hypothesised relationships between the variables were tested using PLS-SEM and SmartPLS software.

Results: The results showed that the effect of the AI-generated personalised content on consumer engagement was significant (0.38, $p < 0.001$). The normative influence has a positive impact on the levels of consumer interaction with companies (0.29, $p < 0.001$). Normative Influence as a moderating factor in the relationship between AI-Driven Personalised Content and consumer engagement is also important (0.12, p-value = 0.03). The research observed that appropriate customised AI content keeps the customers captivated and social and cultural values improve this interaction. Therefore, marketers should integrate AI tools with consideration to values that are accepted in a particular culture to get the best marketing outcomes.

Conclusion: The research implications emphasize the necessity of the ethical and transparent use of AI, the absence of any hidden data, and encourage future research to involve more and more diverse data and analyse consumer confidence in AI-based marketing.

Keywords: Generative AI, personalised content, consumer engagement, destination marketing, normative influence, and artificial intelligence.

1. INTRODUCTION

Generative Artificial Intelligence (AI) is currently one of the most popular innovations in the UK tourism and destination marketing, and it has transformed how travellers explore, plan, and engage with destinations, as (Petrescu & Krishen, 2023) also emphasize. In addition to the increased use of AI technologies in digital marketing, UK tourism organisations are creating personalised, data-driven content that targets a particular consumer segment using generative models (Lv, 2023; Solanki & Khublani, 2024). The relatively strategic improvement in engagement and competitiveness has been made by tourism which adds more than 130 billion to the economy annually and nearly 10 percent of total employment (PwC UK, 2024).

The recent years have witnessed a rapid uptake of AI tools in the UK tourism and hospitality industry, with the use of ChatGPT to generate textual content and DALL-E to generate visual content. The industry is projected to have an AI market of 15.69 billion by 2024 and 20.47 billion by 2025, and its compound annual growth rate (CAGR) is projected to be 30.5% (Research & Markets, 2024). These technologies allow developing hyper-personalised marketing campaigns, which

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may be more interactive and provide more positive customer experiences, including offering travellers personalised itineraries, real-time recommendations and more adaptive booking suggestions, which can significantly enhance interaction and customer satisfaction (Pavlova & Kuzmin, 2024). Approximately 40% of the UK travellers now use generative AI tools in their trip planning, and younger consumers aged 18-34 are the most frequent users (PwC UK, 2024). This tendency indicates the change in the industry towards AI-based personalisation to enhance engagement and conversion.

The increasing integration of personalised content, which is powered by AI, however, comes with a number of challenges. Initially, the dissemination of algorithmically personalized messages can form a filter bubble, reducing the number of people to a set of opinions and influencing biased travel decisions (Rodilosso, 2024). Second, since generative AI produces a lot of automated content, the question of the authenticity and reliability of such information emerged, and consumer trust is questioned (Song *et al.,* 2024). It indicates that despite the growth in the interactions between some consumer groups, other consumers, particularly older travellers, do not necessarily want to be engaged with AI-mediated marketing, which is a demographic difference in the use of technology (Whalen *et al.,* 2024). The difficulty that the UK tourism industry faces, thus, is to utilise the potential of AI in personalising and at the same time deal with its ethical, social, and psychological implications.

The paper will address these issues by discussing how generative AI-generated personalised content affects consumer engagement in destination marketing in the UK and how the moderating variable of normative influence affects this association. The normative influence, which is the tendency to conform to the values and expectations of social groups, is a major factor influencing consumer responses to the AI-mediated marketing messages (Spears, 2021; Jang *et al.,* 2024; Melnyk *et al.,* 2022). This balancing factor should be considered to create effective, socially focused AI-based marketing strategies that will enhance trust and engagement.

Although there has been increasing demand for using AI in marketing tourism products and services, scholarly studies remain scarce in exploring the impacts of generative AI on consumer perception and participation, especially in the context of social and cultural factors (Hollebeek *et al.,* 2024). The research addresses this gap by integrating technological and normative approaches to describe the process of consumer engagement in AI-based destination marketing. This research makes three contributions and is relevant. In theory, it allows extending previous models of social influence in digital marketing, and its interaction of normative influence and AI-personalised content determines consumer engagement. Empirically, it provides evidence on the UK tourism context, where AI adoption is rapidly developing but remains understudied. For policymakers and industry actors, the research can guide the design of ethical, socially responsive AI marketing models that balance innovation, consumer trust, and inclusivity.

The novelty of the given study is threefold. To begin with, previous studies (Lv, 2023; Solanki & Khublani, 2024) have mainly focused on the technological potential or adoption levels of AI tools in tourism marketing and their appeal to various customer segments, without examining normative factors or socio-psychological intermediaries. This paper will focus on the mechanisms by which generative AI-personalised content influences consumer engagement, and a stimulus-organism-response (S-O-R) model will be used to distinguish between the direct impact of the content and the role of socio-psychological intermediaries. Second, it presents normative influence — defined in terms of subjective norms and peer conformity — as a moderating variable, thereby combining the Social Influence Theory with the Technology Acceptance Model (TAM) to understand variation in behaviour in AI-mediated destination marketing. Third, it provides UK-specific empirical data, using a quantitative methodology, to show the influence of generative AI on engagement outcomes. Together, these contributions advance consumer behaviour theory by emphasising the interaction between personalised AI content and social norms to affect engagement in a digital tourism setting.

2. LITERATURE REVIEW

Generative AI development has radically changed destination marketing by enabling the creation of highly tailored content that increases consumer engagement. ChatGPT and DALL-E exemplify generative AI that enables marketers to generate text, images, and videos that are more targeted and personalised to personal preferences and situational prompts (Arora *et al.,* 2024). In the tourism industry, where emotional appeal and experience are key factors, this kind of personalisation enhances consumer loyalty to the destination and satisfaction (Correia & Venciute, 2024). This is due to the fact that precise content customisation is realised since the AI has the capacity to process and decode vast data according to consumer expectations (Bhuiyan, 2024; Arora *et al.,* 2024). Moreover, the new models like Gato by DeepMind show how AI can robotize the content creation and streamline the communication that is related to travel and improve the efficiency of the service and its users (Kim *et al.,* 2025).

According to researchers like (Ray, 2023; and Zhang & Xiong, 2024), overuse of generative AI has the potential to create filter bubbles and algorithmic bias, which supports, rather than challenges, existing attitudes at the cost of content diversity. (Petrescu & Krishen, 2023) argue that AI-generated marketing has ethical and accuracy problems that erode consumer trust once they remain unaddressed in a transparent manner. These findings indicate that despite the fact that AI is becoming more effective in personalisation, its validity and objectivity are paramount in ensuring the continuation of consumer engagement.

Recent studies have also focused on social and cultural processes that can affect the reaction of consumers to AI-based marketing as note (Baek *et al.,* 2024; and Zulfiqar *et al.,* 2024). One of the moderators of this relationship is normative influence, which members of the society have recognised as a measure of what is expected in respect to acceptable behaviours. (Anantrasirichai & Bull, 2022; and Florido-Benítez, & del Alcázar Martínez, 2024) suggest that individuals are more likely to react to the AI-driven messages that are closer to their in-group norms or social acceptance as per the Social Influence Theory and the Social Identity Theory. Similarly, the Theory of Planned Behaviour considers normative influence within the framework of subjective norms, including injunctive norms (what others approve of) and descriptive norms (what others do), both of which, according to (Gupta, 2024), inform consumer reactions to personalised AI content. In tourism, as noted by (Ghani *et al.,* 2022), travellers consider peer opinions and shared social cues as the most significant influences on destination choices. Altogether, the previous research by (Haleem *et al.,* 2022) is unanimous in informing the framework of the current study by showcasing the interactions among technological capability, AI personalisation, ethical integrity, trust, transparency, and social influence, including normative pressures that shape consumer interaction in destination marketing.

2.1. Theoretical Framework

Several established theories, such as the technology acceptance model and the diffusion of innovations theory, underpin the introduction of AI-based marketing. In the Technology Acceptance Model, success is determined by perceived usefulness and perceived ease of use, the two key factors. In the context of generative AI, these factors are the most important in shaping consumers' attitudes toward AI-generated content. According to the results of (Baburao *et al.,* 2024), while customer orientation was found at an acceptable level, it was further identified that consumers are willing to engage with AI-associated content when they perceive it as positively affective, easy to use, and navigational ease. Secondly, (Mbatha, 2024) supported the Diffusion of Innovations Theory, which describes how AI technology diffuses among market players, starting with the first adopters —the innovators —and ending with the last adopters —the laggards. The research indicates that Gen Z have slightly higher behavioural acceptance and perceived satisfaction in AI-synthesised content than older generations (Wang & Chen, 2024).

2.2. Hypotheses

The findings of (Gao *et al.,* 2023) on the effects of AI-based personalisation on consumer engagement are valuable and further elaborate on how the Stimulus-Organism-Response (S-O-R) framework can be extended to incorporate the perceptions of trust, privacy, and usefulness. Empirical validity through the structural equation modelling approach is an advantage for the study. However, the narrow focus on social media is a weakness, as it limits generalisability to other marketing settings, such as tourism, where engagement motifs are more experiential than transactional. Although (Gao *et al.,* 2023) establishes that engagement is mediated by trust and perceived usefulness, the fact that AI personalisation does not directly influence engagement implies that psychological and social factors mediate these relationships to a greater degree than previously thought. From a theoretical perspective, a more profound analysis incorporating Social Influence Theory and Social Identity Theory could be beneficial, as it would explain how group norms and identity-based belonging allow people to trust and interact with AI-personalised stimuli. Therefore, the collective and normative aspects of social embeddedness, which affect participation in socially embedded contexts, are underexplored in the study, even though it is methodologically sound. This weakness suggests the need to shift the focus from individual-level cognitive elements to the role of social norms and collective identity in influencing interactions with AI-personalised information in tourism marketing. This gap is significant in the UK tourism context, where destination selection is frequently socially influenced and culturally mediated. These arguments lead to the formulation of the first hypothesis, H1, of the study that;

H1: Generative AI-driven personalised content statistically and significantly impacts consumer engagement in destination marketing in the tourism sector of the UK.

Synchronised development of Artificial Intelligence-related technologies has led to rapid changes in the need for any special marketing content on the internet. The unique choices and needs of customers are immediately catered to by AI personalisation, which transforms the experience into a more significant one. The content technology of AI in destination marketing allows the creation of content that is appealing to the interests of consumers and results in increased engagement (Soliman & Al Balushi, 2023). Studies indicate that strategies that include AI to create personalised marketing often resulted in more customers valuing it, and a better connection with advertising materials and higher retention rates (Bhuiyan, 2024). The approach of exclusivity would enable marketing to expand its creative range and increase consumer interaction with generative AI.

The content produced by AI can affect the consumer behaviour by analysing the behaviour of individuals in destination marketing (Bhuiyan, 2024). One-off experiences create a connection between the consumers and the site since they reflect their travel needs and preferences. When there is a bond-forming mechanism, the frequency of interaction is enhanced by the information that is directed to their needs. As AI offers certain information, it creates an artificial information gap when it comes to travel preferences, which, consequently, influences interest and engagement. Therefore, these insights confirm hypothesis 1, demonstrating that generative AI-driven personalised content has a positive and significant influence on consumer engagement in destination marketing.

Nevertheless, the positive contribution of AI personalisation is confirmed in the works of (Bhuiyan, 2024; and Soliman & Al Balushi, 2023). However, they emphasise behavioural or transactional engagement indicators, which do not reflect the social and normative processes that determine how consumers perceive and respond to AI-generated content. It is important to realise that this limitation is inherent to consumer engagement in tourism settings, which is necessarily social and influenced by shared values, peer norms, and experiences, as the current study seeks to investigate in more detail.

H2: Normative influence moderates the impact of AI-driven personalised Content on consumer engagement in the context of the UK tourism sector.

The moderating effect of normative beliefs on the association between AI-driven personalised content and consumer engagement is grounded theoretically in the Theory of Planned Behaviour and Social Influence Theory. (Baek *et al.,* 2024) argue that when marketing content is produced with AI tools that adhere to existing social norms and cultural values, it is perceived by consumers as more socially approved and credible. As a result, it leads to amplification of consumer engagement and behaviours. In contrast, when such content deviates from the group's expectations, it leads to weakened consumer engagement, as (Zulfiqar *et al.,* 2024) also stress. Though this moderation effect is statistically small, it is highly significant, as even marginal surges in socially consistent messaging can improve trust, acceptance, and participation across highly competitive tourism markets (Ghani *et al.,* 2022). Nevertheless, the existing literature, including (Baek *et al.,* 2024; and Zulfiqar *et al.,* 2024), does not focus on the normative influence in the context of AI-mediated tourism engagement in particular. The given limitation highlights the topicality of investigating the role of social approval and conformity in influencing consumer reactions to AI-personalised destination marketing in the UK.

3. METHODS

A quantitative approach is used in the study to investigate how personalised content created by generative AI affects consumer engagement in destination branding. The rationale for choosing quantitative is that it involves measurable factors; it can conduct quantitative studies and assess results statistically. According to (Zawacki-Richter *et al.,* 2020), quantitative approaches would be suitable when it comes to identifying the degree to which personalisation and normative influence consumers.

The UK-based tourists who have performed online travel research and booking activities are the target population of this research. The convenience sampling was done through online travel communities and social media (TripAdvisor, Facebook travel groups and Reddit r/travel UK) and through email invitations of tourism-related mailing lists to recruit the participants. The following were the inclusion criteria: the respondent had to be 18 years or older, travelled in the past 12 months, and used online or AI-based tools (*e.g.,* ChatGPT, Expedia Assistant) to plan or book their trips. These were the criteria that made sure that the participants were having the experience in the field of AI-mediated destination marketing. Those who failed to do so or gave unfinished answers were locked out. The population is being targeted because digitally engaged UK tourists are the main target of AI-personalised destination marketing campaigns, which offer the most contextually relevant information on engagement behaviour and social influence processes.

The primary data were collected by asking respondents to complete the survey. Based on the five-point Likert Scale, participants were expected to choose an answer from Strongly Agree (1) to Disagree (5) Strongly (Appendix **A**). The Likert scale is popular in quantitative research because it allows respondents' attitudes and perceptions to be systematically captured, yielding ordinal data suitable for analysis (Thomas, 2021). Content validity was ensured by adapting all measurement constructs to validated scales from previous studies suggested by (Baburao *et al.,* 2024). Some minor wording changes were made to better align with the UK tourism context. Clarity and reliability were tested in a pilot study of 30 respondents before the actual data collection; the Cronbach's alphas were above 0.70, indicating that the internal consistency was valid. Hence, the research undertakes a self-administered online survey to collect data with a range of convenient respondents in line with current practices in quantitative research. The number of variables taken is three: Generative AI-driven personalised content, consumer engagement, and normative influence. The sample size was 356, as power analysis ensured sufficient statistical power for PLS-SEM, accounting for the model's complexity. Though the target sample size was 384 for Cochran's formula for large populations, 356 responses were fully completed and available for analysis. This shortage is warranted, since the response rate did not suffer significantly and the available data complied with the minimum requirements for PLS-SEM, as suggested by (Babii, 2020) as well.

Regarding the model's complexity and the number of indicators, 356 still provides adequate statistical power. Thus, the sample proves adequate for stable structural equation modelling. A priori power analysis (effect size = 0.15, $\alpha = 0.05$, power = 0.95) indicated that a minimum of 138 cases was adequate for the PLS-SEM; therefore, the 356 responses obtained exceeded this requirement. As highlighted by (Ab Hamid *et al.,* 2017), Cochran's formula recommends a sample size of 384 for large populations, and the 356 valid cases provide a strong estimation. This target population comprises UK tourists active in online travel booking across different age groups and travel frequency, providing sufficient representation and generalisation.

In addition, to address potential standard method bias (CMB) arising from the study's cross-sectional design and participants' self-reported data, both statistical and procedural remedies were implemented. Procedurally, confidentiality and anonymity declarations decreased analytical and evaluation apprehension. Statistically, as suggested by (Baburao *et al.,* 2024), Harman's single-factor test indicated that the first factor accounted for merely 32% of the aggregate variance, below the 50% threshold, which validates the absence of a significant CMB. Moreover, as suggested by (Baek *et al.,* 2024), values of the variance inflation factor (VIF) below 3.3 additionally verified the absence of common method bias and multicollinearity.

The analysis is performed using SmartPLS, which enables path modelling in PLS-SEM. The software enables testing hypotheses related to the positive influence of AI-driven personalised content on consumer engagement, as well as the moderating effect of normative influence. This study applies PLS-SEM because it focuses on differences or variances between variables and allows the study of models with one or more reflective measures, particularly when data are not normally distributed (Babii, 2020). The measurement and structural models were analysed based on the Partial Least Squares - Structural Equation Modelling (PLS-SEM) software SmartPLS (Henseler, 2017). Several guidelines were followed to assess the reliability and validity of the constructs. The reliability of the self-developed measures was assessed using Cronbach's alpha and composite reliability, both of which yielded values over 0.70. All items in each construct were reviewed, ensuring their outer loadings were above 0.70. Average Variance Extracted (AVE) was used to assess convergent validity, with values of 0.50 or higher considered indicative of good convergent validity. To examine discriminant validity, the HTMT (Heterotrait-Monotrait) ratio was used; values of 0.85 or lower indicate distinct constructs.

4. ANALYSIS

4.1. Demographics

The results of this investigation were generated using SmartPLS software. This software is easy to use, and the results are available in the tables below. As per Table **1**, 73% of participants were men, indicating that the study is likely to be subject to gender skew, which may affect its generalisability. The largest age group was 26-35 years, accounting for 47% of respondents, indicating that the study primarily captures the views of working-age young adults. This age group is generally more technologically competent and more likely to interact with AI-powered personalised content. The following largest groups were aged 36-45 years (26.7%) and 45 years or older (23.1%), collectively indicating that close to half of the respondents were middle-aged or older, groups that may hold differing attitudes towards AI technologies. Occupationally, more than half of the respondents (56.1%) worked in the private sector, followed by 22.6% who were government employees. Such occupational breakdowns indicate that most respondents are involved in professional settings, which may affect their use of technology-enabled marketing.

4.2. Measurement Model Using Confirmatory Factor Analysis

Generative AI-Driven Personalised Content using Cronbach's alpha and composite reliability. Construct reliability is evaluated with Cronbach's alpha and composite reliability. Internal consistency reliability outputs are presented in Table **2**. Reliability is established if Cronbach's alpha and composite reliability exceed 0.7 (Kline, 2023). This research demonstrates that Cronbach's alphas for Consumer Engagement Generative, AI-Driven Personalised Content, and Normative Influence exceed 0.844, 0.831, and 0.890, respectively, suggesting reliable constructs. Additionally, composite reliability scores for Consumer Engagement are 0.844 and 0.846, and 0.892 for Normative Influence, indicating excellent reliability.

The researcher ensured the indicators' quality by examining their factor loadings. According to the study, factor loadings above 0.6 are considered credible. The Loadings for all indicators surpass the statistical cut-off shown in Table **2**. Consumer Engagement indicators (CE1, CE2, CE3) register factor loadings of 0.890, 0.929, and 0.882; as do the factor loadings for Generative AI-Driven Personalised Content and Normative Influence, which exceed 0.6, indicating validity.

The study by (Cheung *et al.,* 2024) suggested that AVE values exceeding 0.5 indicate convergent validity. According to Table **2**, the AVE values for Consumer Engagement (0.747), Generative AI-Driven Personalised Content (0.762), and Normative Influence (0.820) all exceed 0.5, validating the constructs' convergence. 53 words clear. All AVE measures indicate high convergent validity, as they indicate that the latent constructs explain most of the variance in their corresponding observed indicators. The findings thus confirm that the measurement model is reliable and valid, and provide a reasonable basis for subsequent structural analysis in this study.

Table 1. Demographics.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	259	73
	Female	97	27
Age Group	18–25 years	11	3.1
	26–35 years	167	47
	36–45 years	95	26.7
	45 years and above	82	23.1
Occupation	Private job	200	56.1
	Government job	81	22.6
	Own business	40	11.2
	Not employed	35	11.7

Table 2. Construct validity and reliability for the constructs of the study.

Constructs	Indicators	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Generative AI-Driven Personalised Content Styles	GAPC1	0.866	0.844	0.844	0.762
	GAPC2	0.899			
	GAPC3	0.853			
Consumer Engagement	CE1	0.809	0.831	0.846	0.747
	CE2	0.908			
	CE3	0.872			
Normative Influence	NI1	0.890	0.890	0.892	0.820
	NI2	0.927			
	NI3	0.900			

According to Table **3**, the research rigorously used the Heterotrait-Monotrait (HTMT) ratio to test the discriminant validity of the engaged constructs, a critical step in demonstrating that each latent variable measures a unique factor in the research model (Ab Hamid *et al.,* 2017). An HTMT value less than 0.85 is the benchmark for valid discriminant validity, indicating that constructs do not intercorrelate and that multicollinearity is suitably handled (Cheung *et al.,* 2024). To evaluate the discriminant validity, the researcher used the HTMT ratio. If one looks at HTMT ratios, they should stay below 0.85 to prove discriminant validity and shed light on multicollinearity. All the ratios in Table **3** are below 0.85, indicating that the constructs exhibit discriminant validity.

Among the variables in Table **3**, Consumer Engagement shows moderate values with Generative AI-Driven Personalised Content (0.599) and Normative Influence (0.531), indicating no issues with discriminant validity. Hence, all HTMT values are under the acceptable range of 0.85, indicating discriminant validity between the constructs.

4.3. Path Analysis

Table **4** displays the Structural Equation Model (SEM) analysis, employed to test the hypothesised interactions between Generative AI-Driven Personalised Content, Normative Influence, and their joint interaction impact on Consumer Engagement. In accordance with methodological guidelines, the analysis included bootstrapping techniques to evaluate the relevance and strength of these path coefficients (Becker *et al.,* 2022). The direct relationship between the Generative AI-Driven Personalised Content and Consumer Engagement is path coefficient $\beta = 0.38$, p-value = 0.00. It means that the positive influence of personalised AI content on consumer engagement is strong and statistically significant. The t-statistics are high, which proves the strength of this effect and confirms the first hypothesis. It means that consumers react more actively and more significantly when the marketing communications are personalised to their interests using generative AI. It aligns with the findings of (Bhuiyan, 2024; and Soliman & Al Balushi, 2023), who both discovered that AI personalisation enhances engagement with personalised, context-based experiences. However, as (Bhuiyan, 2024) discovered a more transactional form of engagement on the basis of relevance and convenience, this is further elaborated in the current study, with a focus on experiential engagement, which implies that in tourism, emotional resonance and identity alignment are of greater importance.

In addition, Normative Influence has a very strong positive effect on Consumer Engagement with a coefficient of 0.29 and p-value of 0.00. This helps to justify the fact that social expectations and peer pressure have a major influence on consumer behaviour on online platforms. The cross-product value of Normative Influence and AI-Driven Personalised Content has a smaller but significant coefficient (= 0.12) and a p-value of 0.03, which means that social norms also moderate the influence of AI-generated content on engagement. The result supports Hypothesis 2 and suggests that consumers are more likely to interact with personalised information that fits their perceived social norms. Therefore, Table **4** demonstrates that, although personalisation by AI alone has a strong effect on engagement, its impact is enhanced in socially conformist settings, which reflects the subtle interplay of the technological and sociocultural determinants in the control of consumer response. These findings further affirm Hypothesis 1, establishing that AI-driven personalised content positively impacts consumer engagement. Normative influence's moderating effect is statistically significant but less in magnitude, lending partial support to Hypothesis 2. Equally, the high moderating power of Normative Influence aligns with (Baek *et al.,* 2024), who found that social endorsement of digital messages increases perceived credibility. In contrast, (Zulfiqar *et al.,* 2024) observed weak moderating effects. Such a difference could indicate the collectivist nature of online travel groups in the UK, where peer pressure and social approval make AI-personalised marketing content more influential.

Table 3. Discriminant validity for variables using the HTMT criterion.

	Consumer Engagement	Generative AI-Driven Personalised Content
Generative AI-Driven Personalised Content	0.599	
Normative Influence	0.531	0.718

Table 4. (SEM) analysis.

Constructs	Coefficient	T-Statistics	*P*-Values
Generative AI-Driven Personalised Content -> Consumer Engagement	0.38***	6.21	0.00
Normative Influence -> Consumer Engagement	0.29***	4.24	0.00
Normative Influence x Generative AI-Driven Personalised Content -> Consumer Engagement	0.12**	2.16	0.03

Note: ****Significant at $p < 0.01$*
***Significant at $p < 0.05$*

4.4. Model Explanatory Power

As shown in Table **5**, the model's explanatory power for Consumer Engagement is indicated by an R-square of 0.308 and an adjusted R-square of 0.302. This means that the independent variables in the research — i.e., generative AI-powered personalised content and normative influence — explain about 30.8% of the variance in Consumer Engagement. The R-squared-adjusted value of 30.2% also attests to the model's strength. At the percentage level, this implies that almost one-third of the determinants of consumer participation in destination marketing are explained by the model, which exhibits moderate explanatory power for how personalised AI content and social norms determine consumer behaviour.

Table 5. Model explanatory power.

Variable	R-Square	R-Square Adjusted
Consumer Engagement	0.308	0.302

5. DISCUSSION

The study explores the effect of generative AI-generated personalised content on consumer engagement in destination marketing in the UK and the moderating effect of normative influence. The first hypothesis was supported by the findings, which revealed that when AI produces personalised content, consumer engagement increases, leading to the acceptance of H1 in the study. It turned out that consumers are more concerned with marketing when the messages are personalized to them by AI using information about their personal interests. This is consistent with previous researchers by (Arora *et al.,* 2024) who emphasised that the ability of AI to process vast amounts of consumer information and generate personalised content improves engagement and satisfaction. Moreover, the findings confirm the conclusions of (Madanchian, 2024), who discovered that personalised content leads to more emotive relationships with consumers, increased curiosity and engagement, which subsequently create loyalty and repeat purchase. Generative AI can be applied to marketers, particularly in the travel sector, where it can help them provide customers with outstanding and current services. It highlights that AI is now more involved in assisting customer-based marketing and it is changing the way destinations are promoted in the UK.

Regarding theory, the results can be applied to the elaboration of the Technology Acceptance Model (TAM) and prove that the perceived usefulness and trust, but not personalisation, are the major factors of engagement. It also supports the Diffusion of Innovation (DOI) theory, which posits that, although AI-generated personalisation is an innovative method of communication, uptake depends on how users perceive the authenticity of the communication and the social approval it receives (Petrescu & Krishen, 2023). Notably, the normative influence does not end with the classic social influence depicted in the Theory of Planned Behaviour (TPB), showing that social conformity and alignment with group norms increase the credibility and emotional appeal of AI-personalised content (Melnyk *et al.,* 2022; Jang *et al.,* 2024).

Engagement responses could also be conditioned by alternative explanations such as algorithmic targeting, novelty effects, or biases in platform selection, suggesting that the effects in question might be situational, as also suggested by (Pavlova & Kuzmin, 2024). In addition, the use of a self-reported, cross-sectional convenience sample introduces the possibility of common-method bias and limits causal inference. In practice, for UK tourism marketers, these findings emphasise ethical and transparent AI personalisation, such as A/B testing to assess social norm congruence, AI-generated content disclosure, and the responsible implementation of normative cues to build trust, authenticity, and long-term involvement in destination marketing.

The second objective examined the moderating role of normative influence on the association between AI-generated personalised content and consumer engagement. The findings show that normative influence has a strong effect on consumer engagement, establishing social norms and peer pressure as strong determinants of consumer behaviour, supporting the second hypothesis. This is consistent with the arguments of (Baek *et al.,* 2024; and Zulfiqar *et al.,* 2024), which highlight that normative pressure affects the adoption and judgment of AI-created advertising content by enhancing compliance with social expectations. Also, the engagement effect of normative influence and AI-personalised content was smaller but positive, which indicates that normative influence mediates the relationship, but the effect is moderate. The findings support the work of (Ghani *et al*., 2022), who reported that receptivity increased with content that was in line with the preferences of social groups, yet that individual variations in the dynamic also exist. The research thus supports the claim that normative impact enhances consumer interaction by assuring social validation and approval, which provokes users to interact more with AI generated content as long as it conforms to their social norms. The relatively less powerful moderating effect, however, indicates that the power of personalised content cannot be explained only by social influence, but it is also determined by intrinsic consumer preferences, which implies a complex interplay of technological and social factors.

This observation underscores the continued relevance of behavioural reactions to social norms and peer pressure in the digital marketing era. In theory, it extends the Theory of Planned Behaviour (TPB) by showing how subjective norms —beliefs about what is socially accepted or practised — can increase the use of AI-personalised messages (Baek *et al.,* 2024; Zulfiqar *et al.,* 2024). Similarly, the results of the Social Identity Theory state that the more content generated with AI is consistent with the group values and identities, the more consumers experience a stronger sense of belonging and trust and get more motivated to act (Ghani *et al.,* 2022). However, the moderating effect also plays a key role, indicating that technological personalisation is likely to positively affect engagement in itself and moderate the normative influence. The influence of normativity might be blocked by perceived authenticity, personal preferences, or algorithmic bias. Pragmatically, the UK tourism marketers have to integrate social alignment testing, with A/B tests to assess normative resonance, and be open on the use of AI (Mai *et al.,* 2023). The socially congruent personalisation and authentic, ethical communication behaviours will be integrated to promote the development of stronger trust and long-term participation without infringing on the autonomy of the consumers.

Further, the research provides useful information on the dynamic relationship between the AI technology and the sociocultural forces in destination marketing. There is empirical evidence that content personalisation with the help of generative AI can enhance interaction, but social norms also influence the reaction of people. Marketers must, therefore, customise AI-driven content practices to suit the interest of the consumers and fit within the cultural and social contexts in which the consumers live. The outcomes also confirm the technology acceptance model (Baburao *et al.,* 2024) and the diffusion of innovations theory (Wang & Chen, 2024) that highlight perceived usefulness, ease of use, social context, and behavioural attention in influencing the adoption of technology. In addition, the issues highlighted by (Petrescu & Krishen, 2023; and Ray, 2023) about filter bubbles and biases refer to the ethical imperative of transparency and variety of content production to maintain consumer confidence.

CONCLUSION

The researchers concluded that consumer engagement in destination marketing in the UK is increased with personalised content created by generative AI. The normative influence is also a central moderator that enhances consumer interaction in the case of social norms being consistent with the personalised AI content. Such conclusions underline the necessity to combine technological innovation and social context to make the marketing as effective as possible.

Moreover, tourism marketers need to incorporate generative AI with culture-sensitive algorithms that map personalised content onto consumers' current social norms. In this way, engagement will increase and trust and acceptance will be generated, particularly within socially led consumer segments. This method ensures that AI-generated content speaks on both personal and collective levels. Additionally, destination marketing organisations need to set ethical AI principles regarding transparency, data protection, and filter-bubble avoidance. Having transparent disclosure practices and user control over the level of personalisation will consolidate consumer confidence and long-term loyalty, while ensuring AI use remains inclusive, precise, and socially accountable. The study expands the current literature on digital consumer behaviour by incorporating AI-based personalisation into models of consumer behaviour, including the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB). It illustrates the contribution of normative influence to cognition of engagement beyond individual cognition, and the relationship between technological innovation and social processes in AI-mediated tourism marketing. In theory, the results refine the TAM by showing that AI-mediated tourism marketing behaviour is not limited to cognitive assessments of usefulness but also includes affective and social processes of trust and belonging. In addition, the subjective norms of TPB are also subject to boundary conditions, suggesting that the impact of socio-cultural moderators on the effectiveness of AI personalisation for consumer engagement is substantial.

LIMITATIONS AND FUTURE DIRECTIONS

One significant limitation of this research is the sample size, which, although sufficient for preliminary analysis, could have been increased to enhance the robustness and generalisability of the findings. A more representative and diverse sample would allow having more confidence in the results and, possibly, discover deeper insights concerning normative influence among different demographics. In addition, convenience sampling and self-report data have heightened the chances of bias and thus limited the representativeness of the sample and validity of the responses. These considerations suggest that the findings should be approached with caution, and future studies should employ more rigorous sampling methods and objective data sources in order to achieve the highest possible validity. The future study can consider the following:

1) Future research should involve randomised experiments in which participants are exposed to AI-generated personalised *versus* non-personalised content, with controlled normative cues (high *versus* low normative framing) to establish causal effects and reduce self-report bias.

2) To test the persistence of engagement and control the novelty effects, researchers ought to integrate survey responses with behavioural data collected at multiple time points.

3) Future studies should use probability-based panels or quota sampling to enhance representativeness and stratified sampling by age or generational cohort (*e.g.,* Gen Z vs older adults) to allow comparative multi-group analysis.

4) It can be illuminated by extending the analysis to other cultural and industry settings, both within and outside the UK tourism sector, to understand how normative influence and AI personalisation interact in diverse social and technological settings.

POLICY IMPLICATIONS

Future studies need to explore the effects of AI-generated personalised content in the long run on consumer behaviour and trust, particularly in multicultural and geographic settings. Further research on larger, more stratified samples will give a more accurate understanding of how demographic variables predetermine AI content acceptance and normative influence. Practically, tourism marketers are challenged to integrate AI personalisation with social norm indicators to develop campaigns that appeal to target markets in a real manner. It will be essential to emphasize ethical issues, such as transparency, privacy, filter-bubble alleviation, to guarantee that consumers will trust AI-based marketing. Also, the research of the role of normative influence on the platforms, such as social media and virtual reality, can open new prospects to enhance consumer engagement. Finally, the combination of technological progress and sociocultural awareness will play a critical role in the successful and sustainable destination marketing strategies in the digital environment.

LIST OF ABBREVIATIONS

AVE	=	Average Variance Extracted
DOI	=	Diffusion of Innovation
SEM	=	Structural Equation Model
S-O-R	=	Stimulus-Organism-Response
TAM	=	Technology Acceptance Model
TPB	=	Theory of Planned Behaviour
VIF	=	Variance Inflation Factor

AUTHOR'S CONTRIBUTION

T.S. has contributed to conceptualization, idea generation, problem statement, methodology, results analysis, results interpretation.

ETHICAL APPROVAL & INFORMED CONSENT

All procedures were carried out in accordance with institutional research ethics committee guidelines and Declaration of Helsinki. Informed consent was obtained from all participants. To ensure participant protection, all data were fully anonymized at the point of collection, and no personal or identifiable data was recorded.

AVAILABILITY OF DATA AND MATERIAL

The data will be made available on reasonable request by contacting the corresponding author [T.S.].

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CONFLICT OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this article.

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DECLARATION OF AI

During the preparation of this work the author used ChatGPT for editing purposes. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the published article.

APPENDIX A

Section A: Demographic Profiles

1) Gender
   a) Male
   b) Female

2) Age
    a) 18–25
    b) 26–35
    c) 36–45
    d) Above 45 years
3) Occupation
    a) Private Job
    b) Government Job
    c) Own Business
    d) Not Employed

Section B

Rate the following based on the 5-point scale as below.

1 = Strongly Agree, 2 = Agree, 3 = Neutral, 4 = Disagree, 5 = Strongly Disagree

	1	2	3	4	5
Generative AI-Driven Personalised Content I feel that the AI-generated personalised travel content I receive matches my individual preferences and interests.					
The personalised travel suggestions created by AI make my destination research easier and more relevant.					
I believe that AI-generated content provides me with unique and useful information that enhances my travel planning experience.					
Consumer Engagement I actively interact with travel marketing content when it is personalised to my needs.					
I feel more motivated to explore travel destinations when the marketing content is tailored specifically for me.					
Personalised AI-generated content increases my interest and involvement in destination marketing campaigns.					
Normative Influence I am more likely to engage with AI-generated travel content if I believe my friends or social group fined it valuable.					
Social norms influence how much I trust and respond to personalised travel marketing messages.					
I tend to accept and interact with personalised travel content when it aligns with the preferences of people important to me.					

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