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Research Article

The Moderating Role of Content Creation Cost on the Relationship Between Generative Adversarial Network (GAN) Usage and Marketing Success in Content Marketing: Empirical Evidence from the Automotive Industry of the UK

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Abstract:

Aims and Objectives: This study investigated the moderating role of content creation cost on the relationship between Generative Adversarial Network (GAN) usage and marketing success of content marketing within the UK automotive industry.

Methods: This study used a quantitative survey of 385 marketing managers in the automotive sector of the UK. SmartPLS was used to analyse the data because of its ability to handle PLS-path modelling.

Results: The findings revealed that behaviour intention to use (B= 0.406, *p*-value = 0.000) and perceived usefulness (B= 0.189, *p*-value = 0.005) has a significant and positive impact on marketing success. Perceived ease of use (B= 0.083, *p*-value = 0.135) has an insignificant impact on marketing success. Furthermore, Content creation cost (B= -0.159, *p*-value = 0.002) shows the significant moderating role on the relationship between perceived ease of use and marketing success. Content creation cost (B= 0.009, *p*-value = 0.907) showed an insignificant moderating role on the relationship between behavioural intention to use and marketing success However, Content creation cost (B= 0.127, *p*-value = 0.111) showed insignificant and positive moderating impact on the relationship between perceived usefulness and marketing success.

Conclusion: These results provide insights into the specific dynamics of technology adoption and content marketing success in the automotive sector, highlighting the importance of behavioural intention over perceived functionality and cost.

Keywords: Content creation cost, generative adversarial network (GAN), marketing success, content marketing, automotive industry, TAM, PU, PEU.

1. INTRODUCTION

The automobile industry plays a crucial role in today's society, providing mobility and driving economic growth. Over the last few years, Artificial Intelligence (AI) has changed the industry at a faster pace in many areas, such as diagnostics, production, autonomous driving, supply chains, and customer touchpoints (Hartmann *et al.,* 2025; McGillicuddy, 2025). One of the recent innovations, Generative Adversarial Networks (GANs), is an interesting development, particularly for marketing and content generation (Bose *et al.,* 2024; Wang, 2024). GANs are a category of AI that produce high-fidelity fake media like pictures and videos by training two neural networks against each other. Their ability to produce real content has made them progressively more valuable in industries that need scalable, dynamic, and customized media, such as car advertising (Hartmann *et al.,* 2025; Hossain, 2024).

According to (McGillicuddy, 2025), the contemporary automobile customer journey is more complicated and longer than ever before, crossing many digital touch points. Consumers demand highly customised, on-brand content in

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rapid turnaround. Traditional methods of content creation cannot efficiently meet that demand. GANs provide a solution by enabling the automated creation of spec-accurate and customised visual content, like car video commercials, cutting down on production cost and time. For instance, motor point now produces video commercials 200 times quicker with the help of AI, reporting 88% decrease in creative expense through the substitution of traditional car photography with AI-created imagery.

The evolution is especially pertinent in the UK, where car dealerships are being forced to achieve more with less amidst economic uncertainty and increasing digital expectations (Likhitkar *et al.,* 2024). As noted by (McGillicuddy, 2025), marketing departments are now looking for smart solutions that provide outcome-based optimisation, increased conversion rates, and better ROI. Creative solutions powered by AI, like those facilitated by GANs, are assisting dealerships such as Stone Acre Motor Group to achieve a 79% boost in conversion rates and a 300% increase in sales calls from PPC campaigns due to more effective targeting and creative content. Even with these benefits, the expense of adopting AI tools is a limiting factor in adoption. The high upfront costs of AI infrastructure, training, and integration dissuade most small- and medium-sized dealerships. As big players enjoy the advantages of AI-powered ads, cost remains a limiting factor for mass adoption in the industry (Likhitkar *et al.,* 2024). Hence, it is important to study the moderating role of content cost on the relationship of GANs on marketing success is, thus, an essential area of study.

The UK automotive industry is in a crucial stage with increasing customer demand for digital-led, tailored buying experiences coupled with increasing pressures to lower the cost of doing business and optimise marketing effectiveness (Upadhyay *et al.,* 2021). With AI-based technologies like GANs redrawing the rules in global advertising, it is crucial to understand their relevance in the UK market context. This study is timely and requisite to investigate how GANs could enable scalable, affordable content creation that suits UK dealerships facing a very competitive and economically uncertain environment. Through the examination of the moderating effect of costs in creating content, the research offers practical implications for dealerships, marketing professionals, and AI developers seeking to optimise return on investment. Stakeholders like car retailers, digital marketing experts, and policymakers will stand to gain from knowing more about AI-enabled marketing strategies. Overall, the study is helping to push the application of intelligent, result-oriented advertising in harmony with the UK automobile sector's digital transformation agenda.

2. LITERATURE REVIEW

2.1. Technology Acceptance Model

The Technology Acceptance Model (TAM) is a highly accepted model that describes how people end up accepting and utilising new technologies. Established by (Davis, 1989), TAM suggests that there are two primary factors that determine a person's adoption of a technology: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). PU is the extent to which an individual thinks the use of a given system will improve his/her job performance, and PEOU is the extent to which an individual thinks the use of the technology will be effort-free (Gupta, 2024; Jeong *et al.,* 2024; Musa *et al.,* 2024). These beliefs shape users' attitudes toward the technology, which then influence their behavioural intention to use it, hence ending up influencing actual use. In the case of the automobile sector, TAM is particularly important while considering the adoption of AI-based tools like GANs for marketing (Foroughi *et al.,* 2025; Vrontis *et al.,* 2024). Awareness of user acceptance enables companies to create more user-friendly, useful systems corresponding to user expectations, ensuring successful digital transformation.

2.2. Hypothesis Development

The rise of GANs has sparked considerable interest in their applications within content marketing. GANs enable organisations to generate high-quality content automatically, facilitating personalised marketing strategies that can significantly enhance consumer engagement (Jia & Li, 2024). The technology's potential hinges on its perceived usefulness, perceived ease of use, and behavioural intention to use, which can be understood through an established theoretical framework known as TAM (Davis *et al.,* 2024; Tahar *et al.,* 2020).

Perceived Usefulness (PU) is the level of conviction that a particular technology will enhance the user's performance (Nalbant *et al.,* 2023). Some empirical research has studied the link between perceived usefulness and marketing success. (Muazu *et al.,* 2024) conducted a survey of 300 owners of SMEs in Gombe State, Nigeria, employing regression analysis through SPSS, establishing a significant positive link between perceived usefulness and e-marketing intention. The strength of the study is the fact that it applies a statistically powered sample and actual business setting; however, the limitation is the local scope, limiting generalizability outside Gombe State. (Wilson *et al.,* 2021) utilised PLS-SEM on data from 346 computer users from five Chinese cities and found that perceived usefulness had a significant impact on satisfaction, trust, and loyalty. This research's strength is its strict structural equation model and mediation testing, though cross-industry application is restricted by its concentration on the computer industry. (Harrigan *et al.,* 2021) conducted the study using survey of 150 Europeans. It found that perceived usefulness of social media affected trust and purchase intention. Though their synthesis of TAM with consumer socialisation theory is theoretically enriching, the small sample size and restricted geographic coverage diminish statistical power. Based on these findings the following hypothesis is developed;

H1: Perceived Usefulness of Generative Adversarial Network (GAN) has a significant impact on Marketing success in content marketing

Perceived ease of use (PEU) is another determinant affecting the adoption of GAN technology in content marketing. According to (Davis, 1989), perceived ease of use was related to perceived usefulness, and it led to acceptance of the technology in question. In result, usability shall be recognised as a positive, potent factor positively influencing the intention to use new techie tools within marketing contexts (Cho & Sagynov, 2015; Khan, 2023). A number of empirical research has also looked into the impact of ease-of-use perception to drive marketing success. (Suryatenggara & Dahlan, 2022) used Structural Equation Modeling (SEM) through SmartPLS in analysing the data of 255 Gojek users in Jabodetabek, Indonesia. The researchers reported that perceived ease of use has a significant effect on customer satisfaction that then positively contributes to customer loyalty. The research strength is the mediation model and use of the TAM framework in a competitive app-based service industry. It is not diverse in the service quality dimensions, like perceived risk or safety, which restricts its comprehensiveness. (Wilson *et al.,* 2021) examined B2C e-commerce in Indonesia applying PLS-SEM based on 226 valid responses' data. Their research identified perceived ease of use, along with security, as having a strong effect on customer satisfaction and repurchase intention. The emphasis on security introduces practical usability, yet perceived usefulness was not explicitly tested, lessening its commitment to TAM theory. (Muazu *et al.,* 2024) surveyed 300 Gombe State, Nigeria, SME owners utilising SPSS regression analysis and determined that perceived ease of use had a significant effect on e-marketing intentions. While contextually useful for SMEs in developing economies, its geographical focus restricts wider applicability. Overall, these studies uniformly indicate that ease of use perception improves user satisfaction and intention, although each is constrained by scope or missing variables. Based on this, the following hypothesis can be developed;

H2: Perceived Ease of Use of Generative Adversarial Network (GAN) has a significant impact on Marketing success in content marketing

Behavioural intention (BI) to Use is an individual's attitude or willingness to incorporate a specific technology in their activity (Fetzner & Freitas, 2011; Khan, 2023). Empirical studies repeatedly attest that behavioural intention to use technology widely influences marketing success by shaping actual usage and customer satisfaction. (Vărzaru *et al.,* 2021) used an adapted TAM model and examined questionnaire data from Romanian m-commerce consumers using Structural Equation Modeling (SEM). The results identify perceived usefulness and ease of use as positively influencing behavioural intention, which in turn intensifies consumer intention to use, leading to marketing success. Strength of the study is its strong application of SEM and accounting for generational and gender variance, offering subtle insights. Weakness of the study is a geographically localised sample (Romania) and possible self-report bias, which could hinder generalisability.

(Gil-Cordero *et al.,* 2024) tested the intention of 182 Spanish SMEs to implement the Metaverse through PLS-SEM and concluded that behavioural intention is indirectly affected by business satisfaction instead of effort or performance expectancy in isolation. This implies that behavioural intention is an intermediary of successful strategic marketing by lowering uncertainty in new technology adoption. The strength of this research lies in its ground-breaking emphasis on SMEs and immersive technology, but its weakness is a relatively low sample size and experimental setting, which may impact the predictive ability of the model. These differences with (Vărzaru *et al.,* 2021) can be expected because of the different technology contexts (mobile commerce *versus* evolving Metaverse) and sample types (individual consumers *versus* businesses).

(Li *et al.,* 2024) examined 404 designers' adoption intention of AI-generated content tools using PLS-SEM and concluded that behavioural intention is directly enhanced by performance expectancy and social influence but weakened by perceived anxiety and risk. The strength of this wide-ranging model lies in the incorporation of emerging psychological variables such as anxiety, but it is restricted by its application to a niche group (design professionals and students), which cannot easily be extrapolated to broader markets. The variation of results from the other two studies could be due to the specific emotional and cognitive hurdles of AI aids in contrast with more mature technologies. These studies emphasise the role of behavioural intention in transforming user attitudes into real adoption, hence directly affecting success in marketing. Variations in opinion among studies are mainly the result of differences in technology type, user population, and environmental factors affecting the development of behavioural intention. Therefore, it can be hypothesised that;

H3: Behavioural Intention to Use Generative Adversarial Network (GAN) has a significant impact on Marketing success in content marketing

The conceptualisation of content marketing is comprehensive, and marketers already pinpoint a wide range of indicators for evaluating marketing success in utilising content. (Bubphapant & Brandão, 2024) underlined the necessity of defining key marketing performance indicators reflecting the brand's functioning in achieving the strategic goals. Such activities may include customer outreach, brand recognition, conversion ratios, and customer loyalty, all regarded as the content marketing evaluation metrics (Nalbant *et al.,* 2023). In today's fast-growing world with changing digital dimension, it is essential for a brand to create value and engagement and to build a relationship with the target public (Ho *et al.,* 2020; Musa *et al.,* 2024). With the help of broad performance indicators, marketers are allowed to learn as much as possible about the quality of the content they are utilizing for the campaigns, which can help enhance trends and results.

Additionally, content marketing's contribution to overall marketing success is explained in greater detail based on recognising the content's ability to influence customer loyalty and advocacy. According to (Nalbant *et al.,* 2023), the content marketing strategy needs to ensure that the customers are connected with it to become loyal to the brands and achieve customer value in the long run. It is imperative in automotive industry which involve many decision variables that need information to be processed before making a decision (Davis, 1989). This is because content that is presented in an engaging and informative manner, goes a long way in ensuring that potential customers are well-educated and informed to make a decision that would prove to be exemplary as far as goodwill and brand image are concerned (Bubphapant & Brandão, 2024; Shevchyk, 2024). Therefore, it can be hypotehsised that;

H4: Content Creation Cost moderates the relationship between Generative Adversarial Network (GAN) usage (PU, PEU, BI to Use) and Marketing success in content marketing

2.3. Literature Gap

From the above empirical review, there is a clear gap in the literature concerned with the combined effect of perceived ease of use, perceived usefulness, and behavioural intention to use. GANs have been considered in terms of marketing success, with content creation cost serving as a moderating variable. Whereas earlier research has significantly examined these variables separately in situations such as m-commerce (Vărzaru *et al.,* 2021), AI-supported design aids (Li *et al.,* 2024), and Metaverse adoption (Gil-Cordero *et al.,* 2024), none of them specifically talk about GAN adoption in marketing or analyse the impact of cost on this relationship. Previous literature is weak in examining how behavioural intention is translated into marketing effectiveness with GANs for automated content generation. Additionally, cost as a moderating variable, essential in actual marketing choices, is not adequately researched. Therefore, this research bridges an essential gap by incorporating technology acceptance variables to impact marketing performance outcomes, in addition to presenting content creation cost as a pragmatic and strategic factor in GAN adoption.

2.4. Conceptual Framework

Fig. (**1**) shows the conceptual framework of this study is grounded in the TAM, that integrates perceived usefulness, perceived ease of use and behavioural intention to use to influence marketing success. These factors have been identified to impact on the marketing success in terms of improved efficiency, content quality and customer engagement (Muazu *et al.,* 2024). The framework also indicates content creation cost as a moderating variable, evaluating how cost influences the strength of the relationship between behavioural intention and marketing success. The model provides comprehensive view of both technological acceptance and practical constraints to drive effective adoption of GANs in marketing practices.

3. METHODOLOGY

3.1. Research Design, Sample and Data Collection

This study adopted a quantitative research approach to examine the interaction between GAN usage and marketing success, with content creation cost as a moderating factor. A structured survey questionnaire was designed and distributed among 600 participants in the UK automotive industry. The marketing managers of UK automotive industry were approached using LinkedIn, personal contacts, referrals and personal visit to their sites. These people were selected based on their specialisation in various industries and their positions, which enabled them to facilitate and inform the current marketing strategies and the trends in automotive content marketing. Out of 600, 389 participants filled the survey giving response rate of 64.8%. After removing the missing values, 385 responses were considered valid.

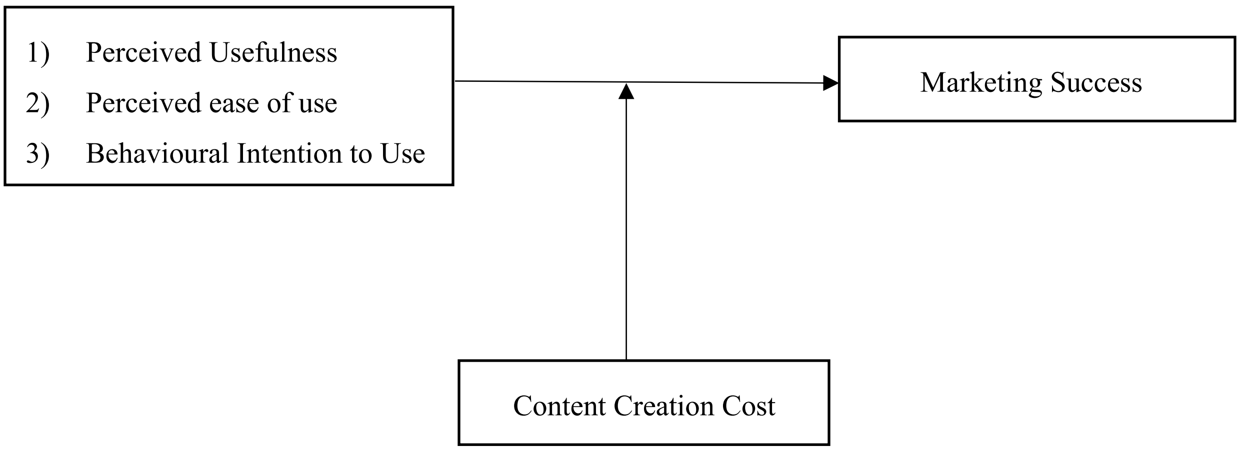

Fig. (1). Conceptual framework.

The survey questionnaire was developed based on the five-point Likert Scale. Regarding the independent variable, the questionnaire statements for GAN usage comprised items that were borrowed from the Technology acceptance model (TAM) set out by (Davis, 1989). The constructs of this model, including PU, PEU and BI, were used to develop propositions on how users believe or perceive the value and ease of implementing GAN technology in marketing. Three items for each of the constructs were used. The dependent variable (DV), marketing success in content marketing measures, was adopted from (Grønholdt & Martensen, 2006). The study identifies the most quantitative metrics concerning the investigated dimensions in prior research focusing on mental consumer results, market results, and behavioural customer results. Hence, three items were used for this construct. For example, Mental Consumer Results incorporated items concerning familiarity with a particular brand, satisfaction, and intention to stick with a specific brand. Market Results targeted key factors such as sales curve, market position, and conversion ratios. Behavioural Customer Results touched upon such indicators as customer loyalty, churn rate, and share of wallet. For the moderating variable, content creation cost, the researchers used the Model of Perceived Sacrifice by (Zeithaml, 1988) to make the questionnaire's statements. In this model, perceived value consists of sacrifice components, which are monetary and non-monetary. However, for this research, the monetary aspect of the model, *i.e.,* the financial cost of content creation (using three items), was considered when designing the questionnaire items. The questionnaire is attached in Appendix **A**.

3.2. Addressing Biases in Research

There are certain potential biases in the research which can influence on the transparency of the study and it is important to address those biases. The selection bias is one of the significant aspects when using the convenience sampling. This bias is reduced by having the participants recruited through several methods such as LinkedIn, personal contacts, referrals and personal visit to the offices. As per (Abobakr *et al.,* 2024), the participants selected based on different platforms ensure that the sampling is bias free. Hence, the selection of the participants has been transparent involving different individuals as much as possible to ensure that diverse opinions are obtained.

Common method bias is also the most crucial that can occur when same method is considered for measuring independent and dependent variables (Podsakoff *et al.,* 2024). The bias is detected and mitigated using the Harman's single factor test. As per this, exploratory factor analysis (EFA) is tested on the entire items extracting a single factor. The total variance extracted for the first factor must be below 50% to indicate that common method bias is not present (Aguirre-Urreta & Hu, 2019; Baumgartner *et al.,* 2021). As per the results of EFA, the total variance extracted for the first factor is 44.385% showing value less than 50%. Hence, the common method bias is not the issue in this study.

The non-response bias is also one of the crucial aspects for the studies when the response rate in itself is low. The study of (Postema *et al.,* 2024) indicated that non-response bias can be evaluated by checking the difference between early and late respondents since late respondents are similar in attributes to the non-respondents. Hence, first 30 participants were considered as early respondents while last 30 respondents were considered as late respondents. The independent sample t-test was used for comparing the statistical difference between early respondents and late respondents. The results shown that PU (MD = 0.15, *p*-value = 0.555), PEU

(MD = 0.28, p-value = 0.15), BI (MD = 0.13, p-value = 0.626), CCC (MD = -0.06, p-value = 0.804), MS (MD = 0.33, p-value = 0.162) has insignificant mean difference. These values of mean difference and significance shows that the constructs are insignificantly different for early and late respondents and hence non-response bias does not exist.

3.3. Data Analysis

SmartPLS was used to employ Partial Least Squares Structural Equation Modeling (PLS-SEM) to make data interpretation and analyse the interconnected relation patterns of the variables in Fig. (**1**). This technique was most appropriate for this analysis due to its ability to test models with many predictor variables and its high efficiency in models with large sample sizes while still providing accurate results. A path analysis model under the PLS-SEM methodology was applied to conduct an elaborate hypothesis test regarding the relationship between GAN usage and marketing success in content marketing to analyse the direct and indirect cross relations between these variables. This analysis using the PLS-SEM approach enabled the consideration of measurement and the structural models. Measurement model uses factor loadings (FL), cronbach's alpha (CA), composite reliability (CR), Average Variance Extracted (AVE) and Discriminant validity to ensure reliability and validity. Structural model uses path analysis to confirm the hypothesis testing.

4. RESULTS

4.1. Demographic Profile

Table **1** reflects the demographic characterisation of respondents of the study. Most of the participants were aged 26–30 years (36%), followed by those between 31–35 years (29%), reflecting a prevalently young adult population. Males account for 80% of the responders, reflecting an overwhelming gender disparity. In educational attainment, 45% have undergraduate qualifications, 35% postgraduates, and 5% with higher education status, with 15% in other categories of education. This population distribution indicates that the study predominantly included young male participants who are well-schooled and potentially tech-literate, hence representative of the key target users of marketing tools based on GAN.

Table 1. Demographic profile.

Demographic Category	Category	Frequency	Percentage
Age	Up to 25	35	9%
	26-30	139	36%
	31-35	112	29%
	35-40	54	14%
	40-45	31	8%
	Above 45	15	4%
Gender	Male	308	80%
	Female	77	20%
Education	Higher Education	19	5%
	Undergraduate	173	45%
	Postgraduate	135	35%
	Others	58	15%

4.2. Measurement Model Using Confirmatory Factor Analysis

Table **2** below shows the measurement model using CFA. FL is used for indicating the validity of the indicators where value above 0.6 is considered to have valid indicators (Ringle *et al.,* 2015). As shown in Table **2**, all indicators have value of above 0.6. Therefore, there was no need to drop any of the indicators and hence the indicators are valid in measuring their constructs. Furthermore, CA and CR are used to evaluate the reliability of the constructs where value of above 0.7 is deemed to be reliable (Hair *et al.,* 2017). As shown in Table **2**, all constructs have CA and CR value of above 0.7 and hence the constructs are reliable. AVE is further used to evaluate the convergent validity where value of above 0.5 is considered valid (dos Santos & Cirillo, 2023). As per Table **2**, all constructs have AVE value of above 0.5 and hence the constructs have convergent validity.

Table **3** shows the discriminant validity. The discriminant validity ensures that the constructs are distinct to each other and indicators of one construct are not related with the indicators of other constructs. The value of below 0.85 ensures that the model has discriminant validity (Hair *et al.,* 2017). The value below 0.85 for all the constructs as shown in Table **3** indicates that the measurement model is discriminately valid.

Table 2. Measurement model using CFA.

Latent Construct	Indicators	FL	CA	CR	AVE
Behavioural Intention to Use	BIU1	0.889	0.885	0.888	0.814
	BIU2	0.930			
	BIU3	0.886			
Content Creation Cost	CCC1	0.912	0.892	0.909	0.821
	CCC2	0.929			
	CCC3	0.877			
Marketing Success	MS1	0.906	0.899	0.899	0.832
	MS2	0.930			
	MS3	0.900			
Perceived Usefulness	PEU1	0.821	0.837	0.842	0.754
	PEU2	0.911			
	PEU3	0.844			
Perceived ease of use	PU1	0.876	0.823	0.832	0.739
	PU2	0.888			
	PU3	0.840			

Table 3. Discriminant validity.

	Behavioural Intention to Use	Content Creation Cost	Marketing Success	Perceived Usefulness
Content Creation Cost	0.476			
Marketing Success	0.717	0.457		
Perceived Usefulness	0.711	0.250	0.619	
Perceived ease of use	0.485	0.316	0.431	0.590

4.3. Path Analysis

Table **4** below indicates the path analysis to confirm the hypothesis of the study. It shows that BIU (B= 0.406, *p*-value = 0.000) has a significant and positive impact on the marketing success. PU (B= 0.189, *p*-value = 0.005) has a significant and positive impact on the marketing success. PEU (B= 0.083, *p*-value = 0.135) shows that perceived ease of usefulness has an insignificant impact on the marketing success. Furthermore, content creation cost (B= 0.009, *p*-value = .907) shows the insignificant moderating role on the relationship between behavioural intention to use and marketing success. Content creation cost (B= -0.159, *p*-value = 0.002) shows the significant moderating role on the relationship between perceived ease of use and marketing success. However, Content creation cost (B= 0.127, *p*-value = 0.111) shows insignificant and positive moderating impact on the relationship between perceived usefulness and marketing success.

Table 4. Path analysis.

	Path Coefficient	T Statistics	*P* Values
Behavioural Intention to Use -> Marketing Success	0.406***	5.993	0.000
Content Creation Cost -> Marketing Success	0.153**	2.518	0.012
Content Creation Cost x Behavioural Intention to Use -> Marketing Success	0.009	0.116	0.907
Content Creation Cost x Perceived ease of use -> Marketing Success	-0.159***	3.026	0.002
Content Creation Cost x Perceived Usefulness -> Marketing Success	0.127	1.593	0.111
Perceived ease of use -> Marketing Success	0.083	1.494	0.135
Perceived Usefulness -> Marketing Success	0.189***	2.793	0.005

Note: **** significant at 1%; ** significant at 5%*

4.4. Model Explanatory Power

Table **5** shows the model explanatory power. It shows that R-square value is 0.503 or 50.3% which shows that 50.3% of the variation in marketing success is accounted by perceived ease of use, perceived usefulness, behavioural intention to use and content creation cost.

Table 5. Model explanatory power.

	R-Square	R-Square Adjusted
Marketing Success	0.503	0.492

5. DISCUSSION

The results of this research unveil subtle information regarding the effect of technology acceptance factors towards marketing success in using Generative Adversarial Networks (GANs) in the UK automobile industry. Most notably, behavioural intention to use (BIU) was the most significant predictor of marketing performance, consistent with the wider literature like (Vărzaru *et al.,* 2021) and Li *et al.,* 2024), both of whom established BIU as a significant driver of the adoption of technology and hence the outcome of subsequent marketing. Consistency here indicates that across sectors, high user intent translates into real-world usage and productivity.

Perceived usefulness (PU) was also found to have a significant positive effect on marketing success, resonating with the findings from (Muazu *et al.,* 2024; and Wilson *et al.,* 2021), which also associated PU with trust, satisfaction, and e-marketing intention. The same consistency ascertains that if users feel GANs improve performance, particularly in creating interesting and good quality content, favourable marketing outcomes ensue.

However, perceived ease of use (PEU) was statistically insignificant in this research, contrary to empirical studies such as (Suryatenggara & Dahlan, 2022; and Wilson *et al.,* 2021), where PEU was a prominent driver of satisfaction and intention. This is due to the UK automotive industry being very complex. In contrast to app-based or e-commerce contexts, automotive content creation typically demands technical accuracy, high visual realism, and compliance with regulatory requirements. In such a context, the ease of use of the tool becomes less important than its performance. Automotive marketers can accept a more difficult learning curve if the tool provides high-performance content, downgrading the relative value placed on ease of use.

Additionally, the moderating effect of cost of content creation yielded conflicting results. It was a significant moderator on the link between PEU and marketing success only, suggesting that when prices are high, ease of use is more important, perhaps because easier tools ease the pain of training and iteration. Yet, content creation cost did not moderate the effects of PU significantly, differing from (Gil-Cordero *et al.,* 2024), who highlighted cost and uncertainty in tech uptake. This is likely due to the high UK automotive market's ability to absorb front-end costs in return for long-term brand equity, particularly within premium segments of the market where investment in advanced content tools is seen as a strategic move. Marketing spending in the UK auto industry, particularly premium brands, is guided by strategic motives over long terms and does not necessarily see short-term cost reduction. The high cost of content driven by cutting-edge technologies such as GANs is generally considered an unavoidable cost to preserve brand stature, leadership in innovation, and customer enthusiasm (McGillicuddy, 2025). In contrast with cost-cutting or smaller markets, UK premium car manufacturers are willing to spend upfront on quality, personalization, and leading-edge digital experiences (Hossain, 2024). This cost flexibility diminishes the moderating role of cost in perceived usefulness, since decision-makers are more concerned with the possible marketing effect and brand building, as opposed to the initial investment or immediate budget restrictions.

PRACTICAL AND POLICY IMPLICATIONS

The results of this research have important practice and policy implications for the UK automotive industry and beyond. In practice, car marketers need to focus on developing strong behavioural intention to employ GAN technology, since it has the greatest effect on the success of marketing. Training sessions and awareness campaigns highlighting the performance advantages of GANs can enhance user acceptance and encourage uptake. Since perceived ease of use is deemed insignificant, firms ought to emphasise showing the value and performance of GANs in producing high-quality, engaging content regardless of whether the tools pose a learning effort.

Policy-wise, incentives like tax breaks or grants would be used to promote investment in sophisticated content marketing technologies, acknowledging their strategic importance in maintaining brand competitiveness in high-end automotive markets. Policymakers could also encourage industry standards or best practices in AI-generated content for ethical use and transparency, fostering consumer trust. Encouraging cooperation between technology developers and automotive advertisers could also adapt GAN solutions more to industry requirements, with better usability without loss of performance. By linking pragmatic measures with supportive policies, the UK automotive industry can optimally leverage GAN technology for improved marketing outcomes and retention of its global competitive advantage.

CONCLUSION AND RECOMMENDATION

The purpose of this research is to evaluate the impact of GAN use on the marketing success of automotive sector of the UK considering content creation cost as moderator. This research highlights the indispensable contribution of BIU and PU to propel marketing effectiveness *via* GANs in the UK automotive market. The strong positive influence of BIU and PU verifies that motivation of users and perception of performance improvement are indispensable to effective technology adoption in content marketing. Nonetheless, PEU proved to be non-significant, given the special context of the automotive industry in which quality and performance take precedence over simplicity. Further, cost of content creation moderated only the association between PEU and marketing success, implying that although cost issues might affect usability perception, they do not have a significant effect on how usability or behavioural intention manifest as success. This underscores the premium automobile market's ability to absorb initial expenditures for strategic benefits in brand equity and customer interaction, separating it from other markets where cost sensitivity is greater.

For users, it is advisable to invest in extensive training and awareness programs that boost the usefulness of GAN technology, particularly increasing users' behavioural intention and perception of its utility. Organisations ought to highlight performance gains and content quality over simplicity due to the industry's acceptance of sophistication without simplicity. Marketers must also manage costs of content creation cautiously, especially by incorporating solutions that reduce usability hurdles to maximise resource efficiency. From a policy perspective, government institutions need to take into account incentives promoting the uptake of AI-based marketing tools among automotive firms, appreciating their strategic significance. Standards of ethics in AI application and openness can increase trust. Additionally, promoting cooperation among technology creators and automotive marketers will ensure GAN solutions are adapted to sectoral needs, making them easier to use and more effective. This holistic approach will ensure long-term innovation and competitiveness in the UK automotive industry.

LIMITATIONS AND FUTURE RESEARCH DIRECTION

This research has a number of limitations that should be noted. Firstly, the scope to the UK automotive industry restricts the application of the results to other sectors or geographies. The specific nature of the industry, including high investment capability and premium market focus, might generate outcomes unrepeatable in less capital-intensive settings. Secondly, the cross-sectional design captures things at one point in time, limiting causality to be inferred or changes in perceptions and adoption over time to be observed. Thirdly, the study is mostly based on self-reported information, and this tends to introduce biases like social desirability or inaccurate recall.

Future studies should look to use longitudinal designs to monitor changes in behavioural intention, perceived usefulness, and ease of use over time as GAN technology continues to develop and is further embedded in marketing processes. Broadening the scope to involve several different industries, particularly ones with varying technological preparedness or differing budget levels, would improve external validity. Further, investigation of other moderating variables like organisational culture, technology infrastructure, or regulatory regimes would offer more insight into the adoption patterns of GANs. Lastly, qualitative research through interviews or case studies might enhance quantitative evidence through revelation of subtle barriers and enablers in concrete settings, especially content generation cost and user experience in AI-based marketing technologies.

LIST OF ABBREVIATIONS

GAN	=	Generative Adversarial Network
TAM	=	Technology Acceptance Model
BI	=	Behavioural Intention
PU	=	Perceived Usefulness
PEU	=	Perceived Ease of Use
TPB	=	Theory of Planned Behaviour

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The data will be made available on reasonable request by contacting the corresponding author [C.K.M.].

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

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APPENDIX A: QUESTIONNAIRE

1) **Age**
   a) Up to 25
   b) 26-30
   c) 31-35
   d) 35-40
   e) 40-45
   f) Above 45
2) **Gender**
   a) Male
   b) Female
3) **Education**
   a) Higher Education
   b) Undergraduate
   c) Postgraduate
   d) Others

Rate following statement on the following scale

1= strongly disagree, 2= disagree, 3= neutral, 4= agree, 5= strongly agree

IV- Generative Adversarial Network (GAN) usage

Davis, F.D., 1989. Technology acceptance model: TAM. Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behaviour and Technology Adoption, 205, p. 219.

Dimension	Questionnaire Statements
Perceived Usefulness	1. Using Generative Adversarial Networks (GANs) improves the effectiveness of our marketing strategies.
	2. The implementation of GAN technology significantly increases the productivity of our content creation process.
	3. GANs provide a competitive advantage by enhancing the quality and precision of marketing content.
Perceived Ease of Use	4. Learning to operate GAN technology for content marketing is easy for our team.
	5. Our organization finds it straightforward to integrate GANs into our existing marketing processes.
	6. Using GAN technology in content creation does not require extensive technical skills.
Behavioral Intention to Use	7. We intend to use GAN technology for content creation more frequently in future marketing campaigns.
	8. Our organization is likely to invest more in GAN tools for marketing content development in the next year.
	9. We plan to adopt advanced GAN solutions to enhance our content marketing strategies.

DV- Marketing success in content marketing

Grønholdt, L. & Martensen, A., 2006. Key marketing performance measures. *The Marketing Review*, *6*(3), pp. 243-252.

Questionnaire Statements
1. The use of GAN-generated content has significantly increased our overall sales volume and value.
2. Our GAN-driven content marketing has led to an increase in the number of new customers acquired.
3. The adoption of GAN in content creation has improved our market share in terms of both volume and value.
4. GAN-generated content has resulted in a higher conversion rate from leads to sales.
5. Our customer loyalty and retention have improved due to the personalized content created by GANs.
6. The number of customer complaints has decreased as a result of more targeted and relevant content generated by GANs.
7. GAN-driven content marketing has contributed to an increase in our overall profit and profitability.
8. The use of GANs in content creation has resulted in a positive return on investment (ROI) for our marketing campaigns.

Moderating Variable- Content Creation Cost

Model of perceived sacrifice

Shukla, P., 2010. Effects of perceived sacrifice, quality, value, and satisfaction on behavioral intentions in the service environment. *Services Marketing Quarterly*, *31*(4), pp. 466-484.

Questionnaire Statements
1. The financial investment in using GAN technology for content creation is substantial for our organization.
2. Our organization allocates a significant portion of the budget to content creation using GAN tools.
3. The cost of using GAN technology outweighs the benefits in content creation.
4. The time and effort required to integrate GAN into our content creation processes are substantial.
5. Using GANs for content creation demands significant human resources and technical expertise.
6. The complexity of operating GAN technology increases the overall content creation cost.

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