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INVESTIGATING MARKETING & BRAND COMMUNICATION: AUDIENCE PERCEPTION TOWARDS AI-DRIVEN CONTENT CREATION

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Abstract
This study investigated the impact of AI-driven content creation on marketing and brand communication, specifically focusing on the perception of the audience. Moreover, the moderating effect of age and gender on these relationships was also explored. Purposive sampling method was employed to collect the data from the sample of 350 students from Foundation University Islamabad, using a structured questionnaire. The Unit of analysis was students belonging to different academic departments. The quantitative research method was applied in this research study. For this research, survey analysis was used, and the questionnaire furnished among students. Firstly, missing values, normality was conducted, followed by an examination of the reliability and validity of the survey questionnaire in SPSS. Data were analysed using techniques like linear regression through SPSS revealed that AI-driven content significantly influenced both brand engagement and marketing effectiveness. Additionally, age and gender moderates the relationship between AI driven content creation and audience perception towards marketing and brand communication. The finding of the study suggest that audience perception of AI driven content positively affect the brand communication, with age and gender playing a very significant moderating role.

INTRODUCTION

The evolution of AI technologies has allowed marketers to analyze massive datasets, create highly personalized marketing campaigns, and generate actionable insights for the audience. As digital marketing continues to grow, the assimilation of AI is becoming increasingly critical for companies to stay economical in the ever-changing market landscape. AI has significantly improved marketing policies that often rely on broad ethnographic data and learning campaigns that might not boom with all the audience segments. AI tools can analyze thinking patterns, consumer behaviours, purchasing patterns, and preferences. This could be helpful for marketers to segment their audience efficiently and deliver personalized content that is more likely to gauge and convert customers. For example, AI algorithms can analyze users' data from social networking websites, predict individual preferences and purchasing histories to predict individual preferences, and recommend products accordingly (Loureiro et al., 2021).

Artificial tools can enhance the creative process of generating ideas and drafting user-preference content that marketers can refine and personalize. AI has an effective influence on customer's that goes beyond automation. AI- powered predict customer's trends, likes and preferences, which enable them to create more efficient content. AI has an immense effect on producing personalized messages captivating content (Bünte, 2023).

Artificial Intelligence denotes to the recreation of human intelligence progressions by machines, particularly computer systems, which comprises learning, self-correction and reasoning (Jorzik et al., 2024). AI-driven marketing states to the usage of artificial intelligence technologies to mechanise data analysis, distinguish content, expect consumer behavior, and enhance advertising policies in concurrent (Chen et al., 2021).

A recent study (Jovanovic & Campbell, 2022) indicates that natural language processor technology, essential for generative artificial intelligence, assists in providing the ability to understand and drive natural language writing. Advertisers and marketers advertise personalized ad messages, texts, videos, and images and establish direct interaction with consumers' behaviour and preferences. Furthermore, artificial intelligence aims to create unique content to identify customer patterns (Tunca et al., 2023).

AI plays an essential part in creating content in advertising (Campbell et al., 2022). Several studies have exposed the AI usage to create advertising material. After learning the customer preferences for AI-driven advertisements, McCann World Group Japan recognized the first artificial intelligence creative director role. In addition, Lexus used AI to script advertisements (Bakpayev et al., 2022).

Similarly (Verma et al., 2021) explained that AI has appeared as a transformative strength in big data, and the significance of Artificial intelligence has grown. It has become an integral part of every global marketing entity long term. The new trends in AI-driven automation have substantially changed AI in the landscape.

In digital marketing, Artificial intelligence can recognize faces and objects, offering substantial possible for various business applications. AI plays a essential role in user retention and leading the conversation. This advanced technology can recognize the faces and objects to help and recognize the individuals to identify the objects. AI processes human images like cookies, allowing businesses to offer customized services based on customer preferences. Businesses can guide users toward desired actions by initiating AI Chabot's, interactive web designs, digital email marketing, and other digital solutions. Some companies are investigating with facial recognition to evaluate customers' attitudes and modify product endorsements accordingly (X. Yang et al., 2021).

The ethical implications are also considerable with the usage of AI for content creation and customer service. Concern over data access, algorithmic bias, clearness, and potential misuse of content generated by AI has been emphasised (Gołąb-Andrzejak, 2023). Another research by (T. H. Davenport & Mittal, 2022) highlighted the ethical usage of AI emphasising the importance of human oversight and control, ensuring that the decision remains in human hands. Artificial intelligence promotes cybersecurity and penalizes malicious AI behaviour. The proliferation of (AI) artificial intelligence-enabled content changes how companies create infinite text, images, and videos with speed and accuracy. Yet, there is still a limitation about how such computerised solutions influence customer evaluations of brand experiences across the customer journey. Comprehending the complex association between AI-produced content and customer experience is key to assessing its actual impact (Ameen et al., 2021).

Overall, AI-driven content has proven to be effective for particular tasks, however, this use is not without errors. At least in this manner, the restrictions it will face in terms of personalization of messages may produce materials less influential and less engrossed by humans. Additionally, the use of algorithms may lead to errors or incorrect communications that can harm customers' sentiments (T. Davenport et al., 2020).

Problem Statement

The emergence of Artificial Intelligence in marketing and brand communication is rapidly changing how brands interact with consumers. By transforming how brands communicate with their target audience through personalized experiences and producing high-quality marketing material, AI-driven content creation can change the game. However, the audience perception of AI-driven content remains a complex issue, shaped by factors such as trustworthiness, authenticity, and ethical issues. AI content is gaining acceptance in a growing number of areas, especially around utilitarian products. Yet this reception is mixed, with many consumers questioning whether AI-driven content can offer the same value or authenticity as human-generated content. This presents a significant challenge for brands that are trying to drive AI into their marketing strategies. The research problem communicated in this research is the absence of understanding regarding how audiences perceive AI-driven content and how it influences their purchasing decisions and brand loyalty. Using this insight, algorithms will help brands incorporate AI-driven content into their communication strategies in a manner that builds trust, engagement, and lifelong brand loyalty.

Objectives

The significant objectives of the research are:

1 **To explore audience perceptions of AI-driven content in marketing and brand communication.**

2 To investigate the moderating effect of age and gender on the relationship between AI-driven content and audience perception.

Research Questions

RQ1: **How do audiences perceive AI-driven content in marketing and brand communication?**

RQ2: Whether age and gender moderate the relationship between AI-driven content and audience purchasing decisions?

Hypothesis

H_1: Audiences perceive AI-driven content in marketing and brand communication as positive.

H_2: Audiences perceive AI-driven content in marketing and brand communication as negative.

H_3: Age and gender will moderate the relationship between AI-driven content and audience perception.

The operationalization and conceptualization

Table 1.2: Operational and Conceptual Definitions of Variables

Variables	Researchers/Theorists	Conceptual Definitions	Operational Definitions	Topics
AI-Driven Content	Kietzmann et al. (2018)	AI-driven content refers to marketing and brand communication materials created by AI technologies like machine learning and NLP.	Measured by the perceived level of AI involvement in content like personalized ads and recommendations.	The role of AI in digital marketing.
Perceived Effectiveness	Dehghani & Tumer (2015)	Perceived effectiveness refers to the audience's belief about how well AI-driven content influences behaviour and conveys messages.	Measured via a Likert scale asking consumers how effective AI content is in delivering product information and influencing behaviour.	Impact of content effectiveness on marketing
Consumer Perception	Wang et al. (2021)	Consumer perception refers to the beliefs and	Measured through questions about trust, loyalty, and	Impact of AI-driven content on brand perception

		attitudes consumers hold toward a brand based on exposure to AI-driven content.	emotional connection toward brands using AI content	
Demographic Factors	Choi et al. (2020)	Demographic factors include characteristics like age, gender, education, and location, which can influence perception and behaviour	Measured by collecting demographic data (age, gender, etc.) and analyzing their influence on perceptions of AI content.	Influence of demographic factors on AI perception.

2. Theoretical framework

This paper examines the role of marketing and brand communication and audience perception towards AI-driven content creation. It also explores the implication of artificial intelligence and customer perception towards marketing, integrating the Elaboration Likelihood Model (ELM) and Technology Acceptance Model (TAM) model to address the existing research gap. Artificial intelligence has significantly revolutionized various sectors, including Entertainment, marketing, software design, and communication. Business leverages artificial intelligence for personalized content, automated content generation, and variety (Babatunde et al., 2024).

The ELM by Cacioppo Petty in 1986 suggests that human-created content is more engaging due to its emotional appeal and influence on behaviour and attitudes. Artificial intelligence transformed social media strategies, enhancing content generation, image recognition, personalized recommendations, Chabot's images, speech recognition, and sentiment analysis. These innovations boost customer service, cost reduction, audience targeting, and accuracy (Burlacu, 2023).

The model explains how individuals receive information through central and peripheral routes; dependent on the individual's inspiration and capability to process the information with high elaboration likelihood, individuals deeply process arguments, trusting on their quality. Whereas low elaboration likelihood, individual leads depend on peripheral cues. ELM is usually applied in numerous domains, such as e-commerce, media, and advertising (Fei et al., 2024).

The primary purpose of this model is to consider all the elements of a message, and it explains how people process messages through dual routes. This model highlights how attitude changes based on mood, motivation, and ability. Since individuals may not always comprehensively analyze the brand's message before making the decision, this model helps construct a persuasive message to target the consumers by considering their abilities and motivations (Shahab et al., 2021).

The Elaboration Likelihood Model (ELM) is one of the persuading theories that see a cognitive pathway; the central route involves vigilant investigation of arguments, and the peripheral route count on on emotions and simple cues. The choice of both pathways depends on the consumers' attention, motivation, and cognitive efforts (H. Yang et al., 2022).

Consumer engagement is determined as consumer behaviour toward brands and companies that is cooperative and imaginative. Consumer commitment with the brands exists in every stage, from buying the item, transactions, repurchasing, and endorsing the creation to other consumers to assessing the brands voluntarily (Eslami et al., 2022).

Social media and AI enable the consumers' perception and meeting and their collaboration with brands across space and time. It enables direct communication and allows marketers and companies to use analytical tools to access the audience connection with their brand. Audience connection with the brand relies on reliability, interactivity, and accuracy. Audience interaction is based on perceived credibility, while a marketer's success relies on user engagement. (Barari et al., 2021).

The association between persuasive communication and consumer engagement and perception can be analyzed using the Elaboration Likelihood Model (ELM). From the view of artificial intelligence, the consumer's behaviour is influenced by how content is presented, and structured, affective and cognitive communication factors can help shape audience perception and engagement levels (Lien, 2001).

The Technology Acceptance Model (TAM) model was documented by Fred D. Davis in 1986. This model helps analyze and measure the events that are critical for deciding whether to accept or reject information technology. The Technology Acceptance Model (TAM) is rooted in a social psychological theory regarding user beliefs and their attitude, intentions, and actions which is referred to as user behaviour. This model seeks principally to explain the most critical factors of user behaviour concerning technology acceptance (Muchran & Ahmar, 2019).

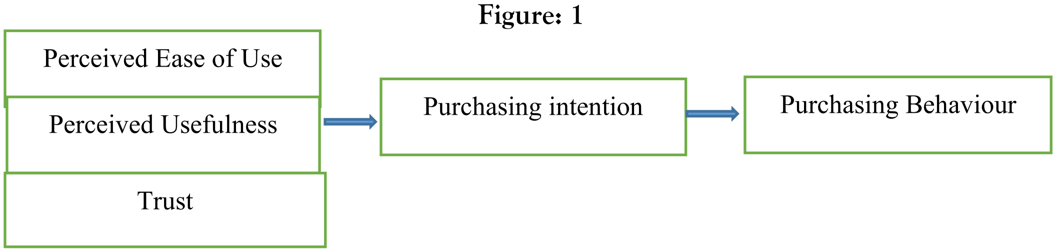
The TAM model seeks to predict the receiving and use of new-generation information systems and technologies by society and to identify the factors affecting the process of technology acceptance (Davis et al., 1989). Since the publication of the TAM (Technology Acceptance Model), it has remained the focal framework commonly used to model technology and the Internet of Things acceptance. In addition, it is a popular concept that appears in research that examines the relationship between individual behaviour, intentions, and technology (Kamal et al., 2020).

This model (TAM) takes into consideration the reasons technology was used, as well as the user's level of acceptance towards the particular form of technology. This model has been useful in various marketing contexts to describe the demand consumers have for innovative technology-based products and services. It will aid marketers in apprehending successful marketing strategies that will help them formulate intelligent marketing plans to get high rates of adoption and usage (Musa et al., 2024).

The model is a significant individual-level framework for clarify the acceptance of technology and has been a widely used theoretical lens for the acceptance of digital products. The technology acceptance model (tam): the use of perceived utility and supposed comfort of use for systems operation as a modeling tool for understanding user adoption of new technologies. Nevertheless, we argue that consumer acceptance of marketing on social media can be studied through the lens of the TAM, and the proposal effects on purchase intention haven't been tested a gaping lack in the social marketing literature (Liu, 2024).

The TAM model is presented in Figure 1 where the arrows represent the proposed causal directional relationships.

Figure: 1



2.1 Literature Review

Creating content driven by artificial intelligence has many promises in this demission to enhance the customer experiences. However, it is crucial to carefully weigh its drawbacks, dilemmas, and possible effects on customer interaction. Marketers may maximize the advantages of artificial intelligence content while reducing its loopholes by comprehending these checklists and successfully addressing them (Anica-Popa et al., 2021).

A recent study by (Jabbour Al Maalouf & Sarkis, 2025) explained that artificial intelligence-driven content is widely used in content making. AI has revolutionized numerous businesses. It involves using algorithms to produce images, text, pictures, and films. In comparison, various activities are efficiently improving the decision-making process. AI-powered automated content production is widely used across various industries, especially in marketing and customer support.

In a research study by (Sindiramutty et al., 2025), ethics are fundamental in the field of AI-driven content, especially regarding preconceptions and biased ideas that might be present in the training data. Prejudiced AI-driven content can damage the company's brand and lead to a lousy customer experience. Therefore, marketing companies must give ethical consideration on a top priority basis by looking at how they train the algorithms on various datasets and appreciate a multipronged strategy for producing inclusive, high-quality AI-driven content.

A recent research study (Jovanovic & Campbell, 2022) indicates that natural language processor technology, which is essential for generative artificial intelligence, assists in providing the ability to understand and drive natural language writing. Advertisers and marketers advertise personalized ad messages, texts, videos, and images and directly interact with consumers' behaviour and preferences. Furthermore, artificial intelligence aims to create unique content to identify customer patterns (Tunca et al., 2023).

Additionally, (Koay et al., 2022) explored that the influencer's competence and trustworthiness significantly predicted customer purchasing intentions for the recommended products or brand. As a result, a customer's positive attitude towards the influencer or marketer might be carried over to the promoted brand or product, increasing its adoption. Researchers further discovered that customer purchase intention was influenced by the influencer's attractiveness and the congruence between the influencer and the recommended brand.

The researcher indicates that the formation of task-performing computer algorithms is known as artificial intelligence (AI). Decision-making, language translation, speech acknowledgment, and visual insight are a few examples of computer algorithms that need human intelligence. Artificial intelligence is deliberately designed to improve over time by learning from data. Furthermore, it states that there are various other methods to define artificial intelligence, including the simulated of all human intellectual capabilities by computers and the artificial of various multifaceted human skills by machines (pp. 20) (Sheikh et al., 2023).

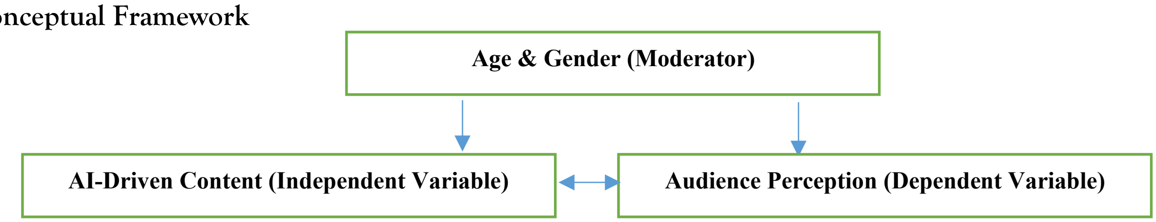
The research (Alpaydin, 2020) defined the subfield of artificial intelligence as machine learning (ML), which is concerned with developing algorithms to let computers learn from the basic data set and gradually get better over time at what they do without explicit programming. Results can be predicted, datasets can be categorized, and patterns can be found using machine learning techniques that help the customer engage with their recommended brand and the marketers. Supervised, unsupervised, and reinforcement learning are some of the various machine learning techniques. Machine learning applications include image recognition, natural language processing (NLM), and predictive analysis. However, machine learning algorithms raise moral and social issues, including the likelihood of biasedness and discernment in machine learning models that may affect the automation of jobs.

The characteristic of artificial intelligence content can be explained as any digital computerized content, such as audio, video, and text images, that are produced by using AI algorithms. These algorithms mimic human-generated content through content creation, data analysis, and trend identification. The example of artificial intelligence-generated content covers the range from tasks like Chabot's automated articles to more complex tasks like creating videos and images (Partadiredja et al., 2020).

A study (Zhan, 2025) found that 60% of consumers are concerned about the authenticity of artificial intelligence. Audiences are often doubtful when the information comes from artificial intelligence. Many consumers believe companies are untrustworthy when using artificial intelligence to create content. This lack of transparency fuels the mistrust about AI-driven whether they are being manipulated, which increases mistrust. Audiences are aware of artificial intelligence's ethical implications, such as bias in algorithms or the potential for AI to replace human jobs. Artificial intelligence enables hyper-personalized marketing. Consumers believe that businesses should be aware of their wants, desires, and needs, but there is a thin line between personalization and privacy invasion. Marketers used to balance personalization with strong data and privacy (Surianinova & Kuvaieva, n.d.).

The three important artificial intelligence modules in advertising content creation are content planning, video creation, and copywriting. First, Artificial intelligence can produce custom images and videos in real time based on customer user data and preferences, providing customers with a more engaging and customized experience (Jovanovic & Campbell, 2022). Secondly, artificial intelligence in copywriting modules can customize advertising material to fit customer behaviour and user preference data. Lastly, in content planning, artificial intelligence can analyze natural language processes for consumer behaviour and customer response on online platforms like social media, assisting in recognising and analyzing data-driven tendencies (Sun et al., 2022).

2.2 Conceptual Framework



3.1 Research Design

This research is based on a quantitative research method and the purpose of this research study is to analyze the impact of artificial intelligence-driven content creation on marketing and brand communication by exploring consumer perceptions. In particular, the research will help by informing our understanding of audience perceptions of AI-driven content concerning trust, engagement, and effectiveness as a tool for brands looking to shape brand communication strategies. Focusing specifically on these perceptions, this study goal is to discover significant trends, preferences, and possible challenges from the brand perspective in implementing AI in marketing efforts. Ultimately, the goal is to deliver actionable insights that can enable brands to further optimize their marketing strategies and create even more meaningful connections with audiences through AI-driven content. Numerical data is used to measure the perceptions, opinions, engagement, and attitudes of the target population. A survey method will be used for the collection of data to identify the correlation among the consumer perception of the brands.

3.1.1 Data collection technique

The primary data collection tool will be a structured questionnaire distributed among the target audience. The question will include close-ended questions with a five-point Likert scale. (e.g., 1- strongly Disagree to 5- Strongly Agree).

3.1.2 Population

Adults aged 18-30 who are active consumers of social media, and who are likely to form their opinions on brands and marketing through AI-driven content and digital interactions.

3.1.3 Sampling Techniques

A purposive sampling technique will be used to ensure the representation across diverse demographic groups in the university, including age, gender, education, and geographic region. This will help to reduce the biases and the aim is to get the sample reflecting the youth population. A sample size of 350 will be used.

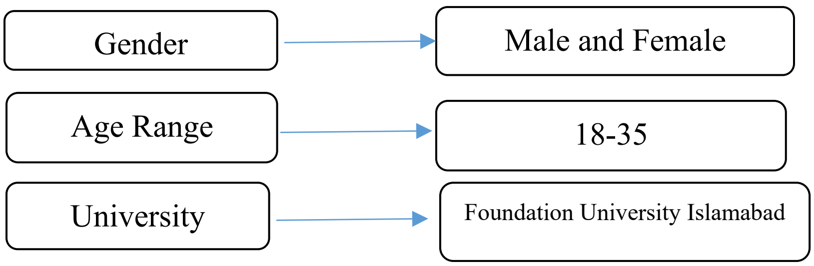
3.1.4 Data Analysis

Quantitative data will be used to analyze the descriptive statistics to summarize consumer perceptions of AI-driven content in marketing and brand communication. Inferential statistics to test the hypothesis regarding the relationship between demographic factors and consumer attitudes toward AI-driven content. Techniques such as **Descriptive Statistics,** and chi-square analysis will be used in this research to explore the strength and direction of this relationship and to assess the impact of AI-driven content on consumer trust, engagement, and audience perception toward brands.

3.1.5 Ethical Consideration
Participants must be fully aware of the purpose of this research, which is to examine their perceptions of AI-driven content in marketing and brand communication. All personal data of the participants will be kept confidential and handled with the utmost care to ensure privacy.

3.1.6 Characteristics of Population.
The following chart highlights the respondents' gender, age, and university.

Figure 1: Characteristics of the Population Demography



3.1.7 Qualification of Respondents.
Table 3, below summarises the qualification-wise breakdown of participating students belonging to sampled universities. 39 from bachelor's degrees, 47 from MPhil students, and PhD 14 students belonging to sampled universities.

Table 1: Frequency Distribution of Educational Qualifications of Participants

Educational Qualification	Frequency	Percent	Valid Percent	Cumulative Percent
Bachelors	39	39	39	39
M/Phil	47	47	47	86
PhD	14	14	14	100
Total	**100**	**100**	**100**	

Data reflect the educational qualifications of participants.

3.1.8 Framing Question for Questionnaire.
The structured questionnaire was developed using a 5-point Likert scale for each construct. Five-point Likert scale "Strongly Disagree, Disagree, Nor Disagree Nor Agree, Agree and Strongly Agree" was utilized.

3.1.9 Pretesting the Questionnaire.
Pilot testing was carried out to improve the instrument for a better understanding of the questions and to achieve the purpose of the survey (Green, 1988). A reliability value of 0.7 was an ideal value (Bagozzi, 1988). Before furnishing the original questionnaire, pretesting was done on the same population. From both universities, a sample of 100 questionnaires was selected. Survey questionnaires were distributed at the university. The researcher got 100 questions without any errors and conducted a pilot study on it.

Table 2: Cronbach's Alpha Reliability Statistics for Pilot Testing

Statistic	Value
Cronbach's Alpha	0.955
Cronbach's Alpha Based on Standardized Items	0.953
Number of Items	27
Cronbach's Alpha (Based on Standardized Items)	35.681
Cronbach's Alpha (Based on Standardized Items)	48.704

Cronbach's alpha reliability was applied to determine the reliability of the scale used in the survey. Table 2 shows that the alpha reliability values of both variables were 0.955 and 0.953, which shows that the data was reliable. Cronbach's alpha reliability was applied to determine the reliability of the scale used in the survey.

3.1.11. Data Coding and Reduction.
After collecting the data, the next step was the reduction of data. In data reduction words and sentences are reduced into categories. Response categories, for instance, the "Male" response, was assigned "1" and the "Female" response was assigned "2" and then entered into the machine. Also, multiple choice answers were given the response, categorized from 1 to 5.

3.1.12. Computer Application in this Research.
The researcher has used statistical software, i.e., Statistical Package for Social Scientists (SPSS Statistics, 23) for analyzing the data. Software MS Word for writing this research study.

3.1.13. Statistical Test.
To analyze the data collected from the survey, the following statistics, i.e., Pearson correlation and regression analysis were used.

3.1.10 Data Collection.
The questionnaires were furnished among students and filled in person by the respondents. The researcher has adopted purposive sampling for survey analysis. The researcher selected the universities, i.e., Foundation University, Islamabad.

3.1.13.1. Pearson Correlation.
The researcher evaluated the Pearson correlation meant to analyze the product-moment correlation between two variables, which measured the similarity of data in the research. The Pearson correlation was used among the variables to examine the relationship between online and offline political participation.

3.1.13.2 Regression Analysis.
The researcher used a statistical method, linear regression to analyze the impact of one variable on another. Moreover, regression analysis was used to analyze how one variable changed when another variable was changed. Regression analysis was applied to show that **AI-driven content** positively impacts **Audience Perception** The Coefficient regression analysis was applied to a model for AI-driven content & Audience perceptions with Gender and age as a moderator and **Perceived Effectiveness as a mediator.**

3.1.13.3 Data Analysis Chart

Hypothesis	Research Questions	Statistical Test Used
H1: Audiences perceive AI-driven content in marketing and brand communication as positive	**RQ1: How do audiences perceive AI-driven content in marketing and brand communication?**	Pearson correlation was used to analyze the relationship between AI-driven content and **Audience Perception.**

H2: Audiences perceive AI-driven content in marketing and brand communication as negative. .	**RQ2:** Whether age and gender moderate the relationship between AI-driven content and audience purchasing decisions?	The Pearson Chi-Square test applied to a model,
H3: Age and gender will moderate the relationship between AI-driven content and audience purchasing decisions.		The Coefficient regression analysis is applied to a model. Gender and age as a moderator. It showed that age and gender moderate the relationship between AI-driven content and audience purchasing decisions which is significant.

Findings
The research was conducted to examine the investigation of marketing & brand communication: the perception of the audience towards AI-driven content creation among the students of Rawalpindi and Islamabad. The data from the selected university was analyzed, and frequency tables were obtained. Below the results were given.

4.1. Survey Analysis Results
For data utilization, SPSS 23 was utilized from the survey. Descriptive statistics were obtained for all the study variables. Cronbach's alpha reliability, mean, and standard deviation were acquired. Pearson Correlation and Regression tests were applied to test the hypothesis.

Table 4.1.1: Frequency Distribution of Participants by Gender

Gender	Frequency	Percent	Valid Percent	Cumulative Percent
Male	168	48	48	48
Female	182	52	52	100
Total	**350**	**100**	**100**	

Table 4.1.1 below summarises the gender-wise breakdown of participating students belonging to sampled universities. Male students filled out 168 questionnaires, and Female students filled out 182 questionnaires belonging to the sampled universities.

Table 4.1.2: Frequency Distribution of Participants by Age Group

Age Group	Frequency	Percent	Valid Percent	Cumulative Percent
18-26	200	57.1	57.1	57.1
27-35	150	42.9	42.9	100.0
Total	**350**	**100.0**	**100.0**	

Table 4.1.2, below summarises the age-wise breakdown of participating students belonging to

sampled universities. 200 students were between the ages of 18-26 years, and 150 were between the ages of 27-35 years of age bracket.

4.2 Exploratory Common Factor Analysis Results (EFA)

The screening of Factor Analysis was an indication of scale development. A exploratory factor analysis was conducted in this research study. (Tang et al., 2025) practically how many latent variables, constructs, and factors are postulated beneath a set of items. It was based on the shared variance between the items and excluded variance that was unique to any of the specific items. Thus, the common factor was the extraction of the standard of the elements, factors that feature all items variance the factors contributing. For the current study, the researcher used an oblique, Promax rotation. Factor analysis items were identified in the solution that was most readily interpretable. Oblique rotation permits the correlation of factors. Here are some examples of scree plot results: For the number of factors, the scree test occur. EFA Scree test using and theoretical base of the scale (eigenvalues > 1, Kaiser Guttman criterion), 1966) extracted 3 factors accounting for 67.816% of total variance for the initial EFA of the online and offline variables. The results of Bartlett's Test of Sphericity were 3637.041 with p <. 001. The suggestion that factor analysis was in order additionally, (Kaiser Meyer Olkin) KMO measure for sampling capability for the data set was. 906 KMO values amongst .8 and. KMO values between 0.8 and 0.9 have been described by Kaiser (1974) as performing exemplary (Salowi et al., 2025).

Table 4.2.1: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.870
Bartlett's Test of Sphericity	Approx. Chi-Square	11500.854
	Df	351
	Sig.	.000

The variables related to one another to run a consequential EFA. The substantial result (Sig. < 0.05) shows matrix is not an identity matrix.

4.2.1.1 Results of Tests for Appropriateness of the Data for Exploratory Factor Analysis (EFA).

The exploratory factor analysis (EFA) was conducted in this study to determine the suitability of the data with two tests: the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (Kaiser & Rice, 1974) and Bartlett's Test of Sphericity (Bartlett). The KMO function in SPSS 27 (Mohanty & Rout, 2025).

4.2.1.2 Bartlett's Test of Sphericity Results.

Bartlett's Test of Sphericity was critical for evaluating the suitability of data for factor analysis. Put differently, it was "the global impact of all correlations in a correlation matrix." Significant values for Bartlett's Test of Sphericity (i.e. p 0.05, at least, some large correlations between the items are sufficient (values >0.20) will be acceptable. Factor analysis looks at the correlations between items and cannot work with too few of these correlations (Camodeca, 2025), Bartlett's Test of Sphericity was significant (i.e.000) in this study, which indicates that the presence of substantial correlations amongst the items is suitable for factor analysis.

4.2.1.3 Kaiser's Criterion Results.

The extraction of initial eigenvalues is presented in Table 4.4.2 as EFA output. Kaiser's criterion states that no factors should be extracted with eigenvalues smaller than 1 (see Table 4.4.2). The two first eigenvalues (which were indicated in bold in Table 4.4.2) were Factor 1 (F1), eigenvalue = 51.590, and Factor 2 (F2), eigenvalue = 63.415. This significance indicated the keeping of the first two common factors.

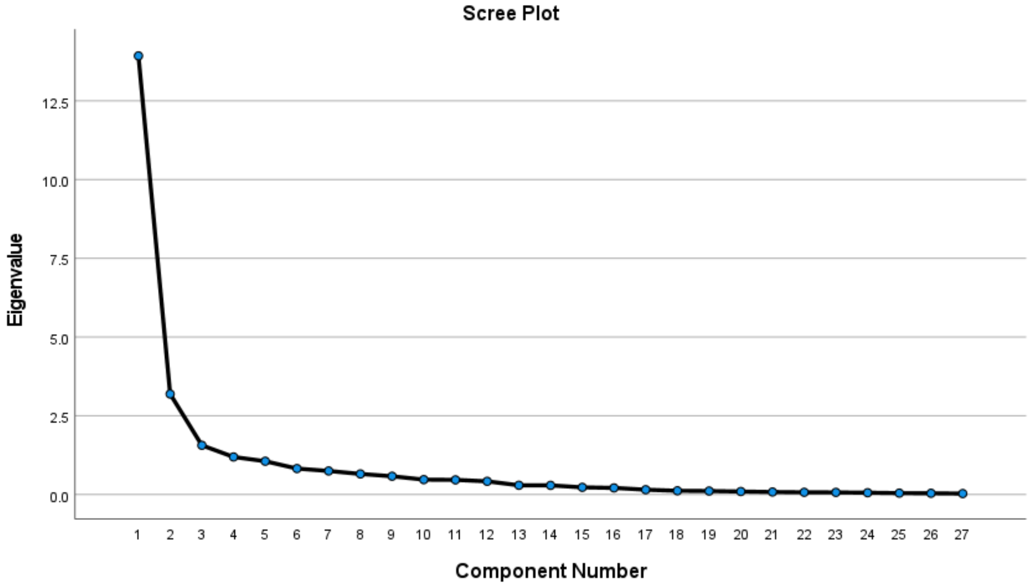
Table 4.2.2:
Factors' Initial Eigenvalues

Factors	Initial Eigenvalues
1	51.590
2	63.415
3	69.205
4	73.624
5	77.542
6	80.595
7	83.369
8	85.791
9	87.942
10	89.696
11	91.420
12	92.974
13	94.062
14	95.139
15	95.987
16	96.766
17	97.335
18	97.777
19	98.190
20	98.545
21	98.845
22	99.108
23	99.361
24	99.574
25	99.741
26	99.888
27	100.00

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

4.2.1.4 Scree Test Results.
Figure 4.2.7 shows the scree plot of the initial eigenvalues for individual likely factor. As shown in Figure 4.1, only the initial eigenvalue for the first factor lies above "the elbow" of eigenvalue plots. These results recognised that only two elements were existing.

Figure 4.2.1
Scree Plot of Factors



4
.2.1.9 Results of Tests for Selecting the Number of Factors to Retain Summary.

The results of the Kaiser criterion and the Scree Plot were not similar (diverging results). Section 5.1: Retained Kaiser's criterion suggestion, →1.0, but contrarily to Kaiser's procedure, the Scree plot suggested retaining only the first two factors. It was also theoretically justified to keep two components since we are performing EFA on two mutually exclusive constructs.

In contrast to Kaiser's criterion, the first 3 factors had eigenvalues above the 1·0 cutoff. The second factor had an eigenvalue of 1.911, and the third factor had an eigenvalue of 1.050. The sameness of any eigenvalue that is small indicates that the variables to which they agree explain only slightly more than any individual variable that contributed to those factors. As to factor analysis, an eigenvalue of 1 indicates that a given item should be viewed as a set to that eigenvalue has falsely applied the formula of Kaiser's criteria by saying, that if any of the factors has an eigenvalue very near to 1.0, that factor that is not retained should be retained.

Table 4.2.3
Complete Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.929	51.590	51.590	13.929	51.590	51.590
2	3.193	11.825	63.415	3.193	11.825	63.415
3	1.563	5.790	69.205	1.563	5.790	69.205
4	1.193	4.419	73.624	1.193	4.419	73.624
5	1.058	3.918	77.542	1.058	3.918	77.542
6	.824	3.053	80.595			
7	.749	2.773	83.369			
8	.654	2.422	85.791			
9	.581	2.151	87.942			
10	.473	1.753	89.696			
11	.466	1.724	91.420			
12	.420	1.554	92.974			
13	.294	1.088	94.062			
14	.291	1.077	95.139			
15	.229	.847	95.987			
16	.211	.780	96.766			
17	.153	.568	97.335			
18	.119	.442	97.777			
19	.112	.413	98.190			
20	.096	.355	98.545			
21	.081	.299	98.845			
22	.071	.263	99.108			
23	.068	.253	99.361			
24	.058	.213	99.574			
25	.045	.167	99.741			
26	.040	.147	99.888			
27	.030	.112	100.000			

Extraction Method: Principal Component Analysis.

When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Table 4.2.3: Communalities

Communalities

	Initial	Extraction
AIDC1	1.000	.705
AIDC2	1.000	.734
AIDC3	1.000	.668
AIDC4	1.000	.758
AIDC5	1.000	.812
AIDC6	1.000	.761
AIDC7	1.000	.763
AIDC8	1.000	.813

AIDC9	1.000	.864
AIDC1	1.000	.715
AIDC1	1.000	.847
AIDC1	1.000	.820
AP1	1.000	.601
AP2	1.000	.692
AP3	1.000	.727
AP4	1.000	.785
AP5	1.000	.825
AP6	1.000	.734
AP7	1.000	.721
AP8	1.000	.794
AP9	1.000	.723
AP10	1.000	.854
AP11	1.000	.889
AP12	1.000	.895
AP13	1.000	.758
AP14	1.000	.851
AP15	1.000	.825

Extraction Method: Principal Component Analysis.

Final communalities represented items' communalities after factor rotation. As publicised in Table 4.2.3, the items' final communalities ranged among .847 and .825. High communalities suggested that items were competent in loading significantly on a factor, which was significant to understanding EFA results (Massad et al., 2025).

4.2.1.9 Discriminant validity

Discriminant validity was the grade to which factors were demonstrated to be orthogonal or uncorrelated. The condition was that a variable must be more strongly related to its factor than to another factor. Two of the most critical methods exist in discriminant validity during an EFA.

Table 4.2.4

Factor Correlation Matrix

Factor	1	2	3	4	5
1	1.000	.619	.558	.738	.253
2	.619	1.000	.497	.587	.559
3	.558	.497	1.000	.577	.217
4	.738	.587	.577	1.000	.211
5	.253	.559	.217	.211	1.000

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.

4.3 Descriptive Statistics

Table 4.3.1: Descriptive Statistics for AIDC and AP

Variable	N	Range	Minimum	Maximum	Mean	Std. Deviation
AIDC	350	46.00	14.00	60.00	41.1657	9.79597
AP	350	60.00	15.00	75.00	49.3829	13.18837

Variable	AIDC	AP
AIDC	1	.911** (p < .001)
AP	.911** (p < .001)	1

Variable	AIDC	AP
AIDC	1	.911** (p < .001)
AP	.911** (p < .001)	1

The descriptive statistics and mean values of variables under study were measured on a five-point Likert scale with one indicating “strongly disagree” to five showing “strongly agree.” The given summary in itself reflects an initial description of the data as a base for consequent comprehensive analyses. The range of all

Table 4.3.2: Reliability and Validity of Statistics (n=350)

The table presents the internal consistency (Cronbach's Alpha) for the constructs under study.

the variables, i.e., AI-Driven content (AIDC) & Audience Perception, (AP) is steady with values between 46 and 60. AI-Driven content (AIDC) value of mean is 41, and & Audience Perception, (AP) value is 49.

Table 4.3.2 indicated the internal consistencies (i.e., coefficient α) of the two constructs under study, and from the results, it was evident that the constructs of the study have reasonable reliability estimates. The results indicated that all the constructs reflect acceptably.

Table 4.3.3: Pearson Correlation among dependent and independent variables

Construct	Number of Items	Cronbach's Alpha
AI-Driven Content (AIDC)	12	0.908
Audience Perception (AP)	15	0.943

Correlation is significant at the 0.01 level (2-tailed).

Table 4.3.3 reports the Pearson correlation between the AI-Driven Content (AIDC) and Audience Perception (AP) variables, based on a sample of 350 participants. The correlation coefficient is $r = 0.911$, indicating a very strong positive linear relationship between AIDC and AP. This suggests that as AIDC increases, AP tends to increase as well. The p-value is reported as $< .001$, representing that this correlation is statistically substantial at the 0.01 level (2-tailed). This means there is a less than 1% probability that this strong correlation occurred by chance.

Table 4.3.4
Summary of AI-driven Content & Audience perception regression model

Figure 4.3.4 showed tone to one linear relationship between AI-driven content & Audience perception, which was tested with the assistance of the linear regression method. The correlation value between AI-driven content & Audience perception, i.e., .911 and R^2 value, which is .831. This value of R^2, i.e., the goodness of fit suggested that .831% variance in audience perception, i.e., the dependent variable, caused by AI-driven content i.e., the independent variable. It showed a significant relationship between both variables.

Table 4.3.5: Chi-Square Test for Hypothesis 2 (Categorical Perception: Positive vs Negative)

Chi-Square Tests					
	Value	Df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	242.308[a]	1	.000		
Continuity Correction	238.954	1	.000		
Likelihood Ratio	308.775	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	241.615	1	.000		
N of Valid Cases	350				
a. 0 cells (0.0%) have an expected count of less than 5. The minimum expected count is 72.00.					
b. Computed only for a 2x2 table					

The Asymptotic Significance (2-sided) for Pearson Chi-Square, Continuity Correction, Likelihood Ratio, Fisher's Exact Test, and Linear-by-Linear Association are all less than 0.001, which specifies strong evidence against the null hypothesis. A p-value of less than 0.05 in each of these tests suggests that the association between the variables is significant.

4.4 Moderation Hypothesis

A hierarchical regression analysis using the **PROCESS ADDON** in SPSS will be conducted to scrutinise the moderating effect of **Age** and **Gender** on the relationship between the independent variable, **AI-driven Content (AIDC)**, and the dependent variable, **Audience perception (AP).**

Model Summary									
					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.911[a]	.831	.830	5.43295	.831	1708.534	1	348	.000
a. Predictors: (Constant), AIDC									
b. Dependent Variable: Audience Perception									

4.4.1 Age as a Moderator between AI-driven content & Audience perception

Table 4.4.1
Coefficient of the regression model for age as a moderator

Model Summary								
				Change Statistics				
R	R Sq	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	p

.930[a]	.865	.864	4.85756	.865	1112.798	2	347	.000
a. Predictors: (Constant), Age, AIDC								
b. Dependent Variable: AP								

For the regression analysis researcher applied the process procedure for SPSS 27 in Table 4.4.1 was the model summary of AI-driven content and audience perception moderation with Age. R^2 was .865, which was significant at p<0.000.

Table 4.4.2

Coefficients						
		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	-10.201	1.481		-6.889	.000
	AIDC	1.273	.027	.946	47.169	.000
	Age	5.015	.534	.188	9.398	.000
a. Dependent Variable: AP						

Table 4.4.2 showed that Age moderates the relationship between AI-driven content & audience perception, which was significant at p < 0.00. Beta value for interaction term i.e. .188 significant at p < 0.00 indicating moderation in effect (Cohen, 2013).

4.4.3 Gender as a moderator between AI-driven content & the audience perception

Model Summary								
				Change Statistics				
R	R Sq	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	p.
.939[a]	.881	.881	4.55329	.881	1290.455	2	347	.000
a. Predictors: (Constant), Gender, AIDC								
b. Dependent Variable: AP								

Table 4.4.3

For the regression analysis researcher applied the process technique for SPSS written by (Hayes, 2012) in Table 4.4.3 was the model summary of AI-driven content & audience perception, and moderation with Gender. R^2 was..881, which was significant at p<0.00.

Table 4.4.4

Coefficients						
		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
	(Constant)	-11.842	1.371		-8.635	.000
	AIDC	1.266	.025	.941	50.475	.000
	Gender	5.985	.491	.227	12.184	.000

a. Dependent Variable: AP

Table 4.4.4 showed that Gender moderates the relationship between AI-driven content and audience perception which was significant at $p < 0.00$. Beta value for interaction term i.e. .227 significant at $p < 0.00$ indicating moderation in effect.

Table 4.5: Summary of the hypothesis
Hypotheses
Results

H_1: Audiences perceive AI-driven content in marketing and brand communication as positive (Supported)

H_2: Audiences perceive AI-driven content in marketing and brand communication as negative. (Rejected)

H_3: Age and gender will moderate the relationship between AI-driven content and audience purchasing decisions. (Supported)

Discussion:

The research study was designed to investigate the investigation & brand communication and the perception of the audience towards AI-driven content creation. Most of the projected results have been consistent with past experimental studies. In this study, the direct effect of audience-perceived AI-driven content in marketing and brand communication has been deeply examined. Moreover, the moderating effect perceived effectiveness was also tested and found to reasonable the strength of the relationship.

To investigate marketing and brand communication was the main objective of the study and to examine the socio-demographic characteristics that influenced it. The perception of the audience towards AI-driven content. For the survey pilot study conducted, the researcher has selected Foundation University Islamabad, selected due to coeducation for equal participation of each gender, i.e., 350 respondents included males and females. For pilot testing, the researcher selected 150 questionnaire samples from the university. The researcher got 100 questions without any error and showed a pilot study to confirm the reliability of the tool.For the survey analysis, a sample of 350 students was selected, 168 males and 182 females from the Foundation University Islamabad, for the data collection the researcher developed the questionnaire and data analyzed through IBM SPSS Statistics 27. Exploratory factor analysis (EFA) was used to test the validity, i.e., convergent and discriminant, along with the reliability of the tool. To provide further verification of the validity and reliability of the scale.

H_1: Audiences perceive AI-driven content in marketing and brand communication as positive.

The statistically significant impact of AI-driven content and audience perception i.e., $\beta = .911$ for $p < 0.01$ with the value of R^2, i.e., the goodness of fit suggested that total variance caused by an independent variable is .831%

H_2: Audiences perceive AI-driven content in marketing and brand communication as negative.

The Pearson Chi-Square Value: is 242.308, with a p-value of 0.000. Asymptotic Significance (2-sided) for all the tests (Pearson Chi-Square, Continuity Correction, Likelihood Ratio, Fisher's Exact Test, Linear-by-Linear Association) is less than 0.001. This p-value being less than 0.05 indicates that the relationship between the variables is statistically significant. Therefore, the null hypothesis is rejected.

H_3: Age and gender will moderate the relationship between AI-driven content and audience perception.

Till now, we talked about direct relationships, i.e., two significant contributors to AI-driven content and audience perception. In this study, the researcher employed age and gender as moderators. In the first case, the researcher checked whether gender moderates the relationship between AI-driven content and audience perception. Age was found to be moderating the relationship between AI-driven content and audience perception. The moderating role of age in the relationship between AI-driven content and audience perception. The results from the regression model specify a significant moderation effect. The R^2 value of 0.865, with an adjusted R^2 of 0.864, demonstrates a strong model fit. The F-change value of 1112.798 ($p < 0.000$) further supports the significance of the model.

Table 4.6.2 provides additional insights into the coefficients for the variables. Specifically, the interaction term for age (β = 0.188) was found to be significant at $p < 0.00$. This suggests that age significantly moderates the relationship between AI-driven content and audience perception. The positive coefficient for age (B = 5.015) indicates that as the age of the audience increases, the perceived effectiveness of AI-driven content also increases.

Gender as a Moderator the second part of the examination explored the moderating role of gender in the same relationship. The results from the regression model presented that gender also plays a substantial moderating role. The R^2 value for this model was 0.881, with an adjusted R^2 of 0.881, indicating an excellent fit. The F-change value of 1290.455 ($p < 0.000$) further reinforces the model's statistical significance.

Table 4.7.2 highlights the coefficients of the variables, where the interaction term for gender (β = 0.227) was significant at $p < 0.00$. This suggests that gender moderates the relationship between AI-driven content and audience perception. The positive coefficient for gender (B = 5.985) implies that the relationship between AI-driven content and audience perception is stronger for one gender compared to the other. This finding also supports the moderating role of gender, as indicated by the significant interaction term.

Hence the result indicated from the present study was that gender and age were used as a competent moderator between online and offline political participation, whereas AI-driven content has a positive and significant relationship with audience perception.

5.0 Conclusion

The research paper "Investigating Marketing & Brand Communication: Audience Perception Towards AI-driven Content Creation" investigated how AI-driven content affects the perception of the audience and its influential role in the progress of marketing strategies. The advent of artificial intelligence in content creation has changed the digital marketing sphere and the way businesses connect with customers. This study concentrated on examining the audience's perception of AI-driven content and its brand communication effectiveness.

The results suggest that AI-driven content contributes positively to brand attitude (credibility, engagement, and relatability). Demographic variables (age and gender) also proved to moderate the interaction between AI-driven content and attitude toward the character. Younger participants tended to trust and feel related to AI-driven content and were more likely to engage with it, also the gender aspect affected the perception of the content and their trust and emotive commitment relation with the AI. This is indicative of the increased role that AI is playing in the world of marketing, by providing custom content for different audiences.

However, the study also discovered some challenges, including concerns about the truthfulness of AI-driven content and its capability to build long-term brand loyalty. While AI can enhance content production, its effectiveness pivots on the transparency of its usage and the balance between mechanization and human connection.

5.1 Recommendations

Following are the recommendations for the concerned scholars and academicians.

1) **The** study concentrated on a specific group of audience, and future research could broaden the demographic across industries and different regions. This study is cross-sectional design which provides the audience's perception at one point in time. To gain deeper insights into how AI-driven content evolves, future research should adopt a longitudinal study.
2) This study is centered on a quantitative method, incorporating methods such as focus groups, and interviews can provide a better understanding of the underlying reasons behind audience perception of AI-driven content.
3) AI-driven content become increasingly integrated into marketing strategies, and and brands need to maintain transparency about their use of AI. Brands should work to ensure their AI content remains ethical and free from bias approach, it should ensure accuracy and inclusivity.
4) AI can significantly enhance content creation. It is important to keep the balance between AI-driven and humanized originality. Future research could discover the synergy between AI-driven content and human-led creative content, aiming to create the emotional connection and main authority that human creativity brings.
5) As AI-driven content becomes more predominant, brands should focus on understanding

how AI-driven content can produce long-term relationships with customers. Research should explore how AI-driven content influences not only rapid arrangement but also brand loyalty and advocacy.

By following these recommendations, both researchers and practitioners in the turf of marketing and AI can further expand their sympathetic of the role AI plays in modern marketing and brand communication, pledging that content remains significant, appealing, and morally associated with audience potential.

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