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AI-POWERED DATA VISUALIZATION: A KEY FACTOR IN OPTIMIZING DIGITAL MARKETING DECISIONS

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ABSTRACT

This study investigates the impact of multiple AI-driven data visualization elements on decision-making effectiveness in digital marketing, focusing on Generation Z consumers. The research addresses the significance of AI tools in marketing, particularly in enhancing decision-making processes. While previous studies have examined individual elements, this study combines factors like content clarity, interactive design, real-time insights, predictive visualization, and user accessibility to explore their collective impact. The study addresses a gap in the literature by examining how these elements, when used together, improve decision-making in the digital marketing context. A quantitative correlational approach was used, with a sample of 100 Generation Z consumers who actively engage with digital marketing campaigns. Data were collected via a structured questionnaire with a 5-point Likert scale. SPSS version 26 was used for statistical analysis, including validity testing ($r > 0.195$), reliability testing (Cronbach's Alpha > 0.70), and classical assumption tests. Multiple regression analysis showed that all independent variables significantly influenced decision-making effectiveness, with interactive design ($t = 6.132$, $p < 0.001$) showing the strongest impact, followed by real-time insights ($t = 5.872$, $p < 0.001$). The overall model was significant ($F = 7.845$, $p < 0.001$). This study contributes to social commerce literature by advancing the understanding of AI-driven data visualization tools in digital marketing. It also provides practical implications for businesses seeking to enhance decision-making through AI. The study sets the foundation for future research on the collective impact of multiple marketing elements and evolving technologies.

Keywords: **AI-driven data visualization, decision-making effectiveness, digital marketing, Generation Z, interactive design, real-time insights, predictive visualization, social commerce.**

1. INTRODUCTION

In today's data-dominated world, businesses are increasingly dependent on digital marketing to capture consumer attention, increase brand visibility, and drive revenue (Chen et al., 2021). As digital platforms continue to expand, marketers are now confronted with a tremendous influx of consumer and behavioral data from a multitude of sources—ranging from social media platforms and websites to CRM systems and e-commerce databases (Judijanto et al., 2024; Mulyono & Rolando, 2024a). This explosion of data provides unparalleled opportunities for insight generation, but it also introduces significant challenges in terms of data interpretation, decision-making speed, and strategic alignment (Mulyono & Rolando, 2024b; Rolando & Mulyono, 2024; Rolando & Wigayha, 2024). Traditional analytical tools and reporting methods are often insufficient to keep pace with the speed, scale, and complexity of modern data environments. As such, advanced technologies are increasingly being explored to enhance marketers' capabilities in making faster, more accurate, and more insightful decisions (Abbas & Ali, 2024).

One of the most promising innovations in this area is the use of artificial intelligence (AI) to power data visualization tools. Unlike conventional visualization platforms that rely heavily on manual input and static display, AI-driven data visualization tools dynamically interpret data, identify patterns, and present insights in real-time through interactive interfaces (Rahardja et al., 2024; Rolando, 2024). These tools help marketers not only understand historical trends but also forecast future outcomes and respond swiftly to emerging market signals (Chen et al., 2021). AI-based visual analytics can significantly enhance the cognitive comprehension of complex data by organizing it into intuitive visuals that are easy to explore, manipulate, and interpret (Maha et al., 2024; Mulyono, Ingriana, et al., 2024). This technological evolution marks a critical turning point in how data is used in marketing decision-making—not just as a retrospective tool but as a strategic partner in forward-thinking business choices (Zhang et al., 2024).

Despite the growing availability and popularity of AI-based tools in the market, there is still limited academic exploration into how these tools influence actual decision-making processes in digital marketing contexts (Ingriana, Chondro, et al., 2024; Wigayha et al., 2024). While the fields of business intelligence, marketing analytics, and decision sciences have made significant strides in analyzing the broader impact of data and AI, the specific role of visual interfaces powered by AI remains underexplored (Mulyono, Hartanti, et al., 2024; Rolando & Ingriana, 2024). Most studies have either focused on data analytics capabilities in general or examined AI in operational capacities such as chatbots, personalization engines, and automation (Ingriana, Gianina Prajitno, et al., 2024; Putri & Setiawan, 2025; Rolando et al., 2025). Few studies have addressed how visual elements influenced by AI—such as real-time dashboards, predictive graphs, and interactive trend lines—impact human judgment, interpretation, and decision execution in digital marketing activities (Mahi et al.,2024).

The increasing sophistication of digital marketing strategies calls for tools that can support complex decision-making environments where time, accuracy, and insight are critical (Wigayha et al., 2025; Winata & Arma, 2025). Marketers must frequently decide which audiences to target, which messages to prioritize, what platforms to use, and how to allocate budget across multiple channels. These decisions often require the rapid synthesis of multiple variables, including engagement metrics, customer behavior, sales performance, competitive activity, and even macroeconomic indicators (Matúšová et al., 2023). AI-enhanced visualization tools simplify this process by integrating and displaying relevant data in a manner that supports cognitive efficiency and strategic thinking. Yet, despite their potential, these tools are not universally adopted nor fully understood in terms of their actual influence on decision-making effectiveness.

Several prior studies have examined themes adjacent to this topic, such as data analytics in strategic decision-making, the implementation of business intelligence systems, and the organizational readiness for AI adoption (Ingriana, 2025; Tan & Alexia, 2025; Widjaja, 2025; Zahran, 2025). However, many of these works treat visualization as a passive output rather than an active component of the decision-making process. They tend to focus on system architecture, algorithmic efficiency, or organizational outcomes without investigating the user interface or the psychological aspects of how marketers interact with visual information. Moreover, few have explicitly examined the decision-making process itself—how visualized data affects interpretation, confidence, speed, and eventual decision quality (Mahi et al.,2024). This oversight leaves a crucial knowledge gap in understanding how AI-driven data visualizations directly contribute to decision-making performance in digital marketing settings (Rif'an, 2024).

This research seeks to address that gap by focusing on the intersection of AI technology, data visualization, and marketing decision-making behavior. The central research question guiding this study is: to what extent do AI-driven data visualization tools improve the quality, speed, and confidence of decisions made by digital marketing professionals? Answering this question involves exploring both the technical capabilities of such tools and the human responses they provoke. This includes investigating features such as interactivity, automation, adaptability, and predictive visualization, as well as psychological variables like cognitive load, comprehension, trust, and decision confidence. By analyzing these factors in a marketing context, the study aims to generate comprehensive insights into how such tools support or hinder effective decision-making (Bennett,2022).

The rationale for this study stems from the urgent need for organizations to become more agile and responsive in their marketing operations. The modern consumer operates in a fast-paced, multi-channel environment where brand preferences shift quickly, and engagement patterns are highly dynamic. As a result, marketers need to act fast based on accurate, real-time insights. Traditional reporting systems are often too slow, too complex, or too rigid to meet these demands. They require manual analysis, which can introduce human error or delay. In contrast, AI-powered visualization tools offer an automated and dynamic alternative, one that is increasingly necessary as organizations seek competitive advantages through speed, accuracy, and personalization (Mahi et al.,2024).

In addition to enhancing strategic efficiency, AI-driven visualization tools may also democratize access to complex insights. Non-technical users—such as marketing managers, campaign designers, and brand strategists—often struggle with traditional analytics platforms due to their technical complexity. AI-enhanced visualizations, with their intuitive interfaces and natural language processing capabilities, lower the barrier to entry, enabling a wider range of users to access, explore, and act on data insights (Matúšová et al., 2023). This democratization fosters a culture of data-driven decision-making across all levels of the marketing organization, improving coherence, coordination, and overall performance.

This research also explores the cognitive and behavioral dimensions of decision-making when marketers interact with AI-driven visual data tools. It aims to determine whether such tools reduce decision fatigue, improve pattern recognition, and enhance information retention. It will also examine how marketers perceive and trust AI-generated visualizations, and whether this trust correlates with better strategic choices (Wu & Monfort, 2022). These psychological and perceptual variables are essential for understanding not just the functional utility of the tools but also their practical impact on human decision-makers in real-world scenarios.

From a methodological perspective, the study proposes a mixed-method approach. Quantitative data will be collected to measure the impact of AI-driven visualization on decision accuracy, speed, and perceived confidence. At the same time, qualitative data—gathered through interviews, case studies, or open-ended surveys—will be used to capture experiential feedback, emotional responses, and contextual observations from users. This holistic approach allows for a richer understanding of both the outcomes and the mechanisms underlying the adoption and usage of AI-enhanced visual decision tools (Noranee & Othman, 2023).

This study contributes to the academic field in several key ways. First, it enriches the literature on digital marketing analytics by specifically focusing on the role of visualization—a component often neglected in favor of backend data processing or algorithmic development. Second, it introduces an interdisciplinary framework that combines insights from marketing strategy, human-computer interaction, and cognitive psychology. This framework helps to explain how data visualization acts not only as a reporting mechanism but as a cognitive aid that shapes and enhances human decision-making. Third, the research provides empirical data that can guide practitioners in choosing, customizing, and integrating AI-powered visualization tools into their marketing workflows.

Beyond academic contributions, this study also offers valuable implications for practice. Marketing leaders and data scientists can use the findings to better understand the human factors that influence tool adoption and effectiveness. Software developers and analytics vendors can gain insights into design preferences and interface features that maximize usability and impact. Organizational decision-makers can evaluate the return on investment of AI-based visual analytics by linking them directly to measurable outcomes such as campaign performance, audience growth, and customer retention. Finally, educators and training institutions can use the findings to update curricula and training programs to reflect the growing importance of visual reasoning in digital marketing.

The uniqueness of this research lies in its targeted focus on a narrow yet impactful aspect of digital transformation: the role of AI-driven visualization in shaping real-time marketing decisions. Unlike general discussions of big data, business intelligence, or AI automation, this study zeroes in on how visual tools, enhanced by AI, interact with human cognition to improve decision outcomes. It acknowledges the dual nature of these tools—as both technological systems and communication artifacts—and seeks to understand how that duality influences user behavior, performance, and trust.

As digital marketing continues to evolve, the role of AI will inevitably become more pronounced. But the success of AI in this domain will not be determined solely by its computational power. It will also depend on how effectively it communicates with human users—how well it translates complex data into meaningful insights that can be quickly understood, confidently interpreted, and strategically applied. By focusing on this intersection of data, AI, visualization, and decision-making, this research aims to provide a timely and essential contribution to both theory and practice in the age of intelligent marketing.

2. METHODOLOGY

2.1 Methodology Research

This research adopts a quantitative methodology to systematically investigate the influence of AI-driven data visualization tools on digital marketing decision making. Quantitative research enables objective measurement and analysis of variables through the collection of numerical data and application of statistical tools. This approach is appropriate given the study's objective to identify the extent to which AI-powered visualization variables affect decision outcomes. The research employs a cross-sectional design and utilizes a structured survey distributed to digital marketing professionals. This design allows data to be collected at a single point in time from a sample that represents the population of interest. The use of a cross-sectional design also facilitates the identification of existing relationships between constructs without manipulating variables, preserving the natural conditions of the environment (Mahi et al.,2024).

This study is rooted in a deductive research paradigm, where existing theories and findings in the literature are used to derive hypotheses, which are then empirically tested. The goal is to test causal relationships between independent and dependent variables in a structured manner using inferential statistics. The research process involves designing the survey instrument, conducting a pilot study to ensure reliability and validity, collecting data, and analyzing the results using SPSS version 26. This structured framework enables replicability and objectivity, hallmarks of scientific inquiry in quantitative research.

2.2 Conceptual Framework

The conceptual framework for this study is constructed to identify the impact of several independent variables on a single dependent variable. The independent variables are derived from key AI-driven visualization characteristics and include Content Clarity (X1), Interactive Design (X2), Real-Time Insights (X3), Predictive Visualization (X4), and User Accessibility (X5). The dependent variable is Decision-Making Effectiveness (Y), defined as the extent to which digital marketing decisions are improved in terms of accuracy, confidence, and speed.

The proposed model for the relationship is:

$PI = \alpha + \beta 1C + \beta 2SP + \beta 3I + \beta 4V + \beta 5L + \varepsilon$

Where:

PI = Purchase Intention (used synonymously with Decision-Making Effectiveness in this context),
α = constant
β1–β5 = regression coefficients
C = Content Clarity
SP = Special Features (represented by Interactive Design)
I = Real-Time Insights,
V = Predictive Visualization
L = User Accessibility,
ε = error term.

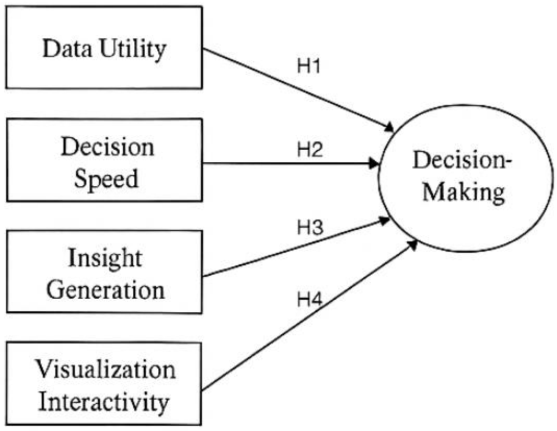

Figure 1. Conceptual Framework

A graphical representation showing directional arrows from Content Clarity, Interactive Design, Real-Time Insights, Predictive Visualization, and User Accessibility all pointing to Decision-Making Effectiveness (Purchase Intention). Each arrow represents a hypothesis, labeled H1 through H5.

This conceptual framework integrates key theoretical and practical dimensions in the study of AI-driven data visualization and its impact on decision-making. Each independent variable was selected based on previous empirical research and theoretical propositions identifying what characteristics enhance the effectiveness of data visualization tools. For instance, Content Clarity focuses on the simplicity and readability of visualized data, while Interactive Design emphasizes the dynamic interface allowing users to explore information more deeply. Real-Time Insights stress the importance of up-to-date data availability, and

Predictive Visualization extends decision-making support by enabling forecasting. User Accessibility targets inclusivity and the ease of use of these tools. Together, these components form a multi-dimensional perspective for evaluating how visualization tools influence marketing decisions, providing a rich framework to test specific hypotheses and validate theoretical expectations. This model also serves as the basis for designing research instruments and statistical analysis, ensuring coherence between theoretical constructs and empirical measurement (Dimara et al., 2022).

2.3 Sampel

The target population for this study comprises digital marketing professionals and practitioners who actively use or are familiar with AI-powered data visualization tools. These individuals are primarily employed in marketing departments, digital agencies, e-commerce firms, and organizations that invest in data-driven decision making (Liu & Xie, 2023). By focusing on respondents who possess knowledge and experience in utilizing AI in marketing analytics, the study ensures that data collected reflect accurate assessments of the influence these tools have on their decision-making processes. The research recognizes the importance of obtaining insights from individuals who operate in a practical, real-world digital marketing environment (Zhang&Sun, 2022).

To determine the appropriate sample size, the Lemeshow formula is employed as it provides a reliable method for estimating sample size for proportions with specified confidence levels. The formula is:

$$n = Z^2_{1-\alpha/2} * p * (1-p) / d^2$$

- Using a 95% confidence level
- Z = 1.96, a proportion (p) of 0.5 is assumed to account for maximum variability, and the margin of error (d) is set at 0.05.

The resulting calculation is:

$$n = (1.96)^2 * 0.5 * (1 - 0.5) / (0.05)^2 = 384.16$$

This result is rounded up to 385 to ensure that the sample is large enough to yield statistically significant results and allow for generalization to the larger population of digital marketers. The actual sample to be collected may exceed 385 to account for incomplete or invalid responses and to improve the robustness of the analysis.

A non-probability purposive sampling technique is used in this study due to the specificity of the respondent criteria. Participants are selected based on their expertise, usage frequency of AI-driven visualization platforms, and availability. This sampling technique is justified because the research focuses on a particular group with unique insights that cannot be captured through random sampling of the general population. Furthermore, purposive sampling ensures the inclusion of individuals who are most likely to provide meaningful and relevant data for addressing the research objectives (Chen et al., 2021).

Data will be collected via an online structured questionnaire distributed through professional networks, LinkedIn communities, marketing associations, and digital marketing forums. An introductory statement outlining the study's purpose, voluntary participation, and confidentiality assurance will precede the survey to promote transparency and encourage informed consent. By utilizing digital channels for data collection, the research aligns with the technological context of the study, improving response rates and efficiency (Lawal & Binuyo, 2022).

The use of a large, purposively selected sample of professionals enhances the study's external validity while maintaining the depth and relevance of insights. Moreover, collecting data from multiple industries and regions further enriches the diversity of the dataset, increasing the applicability of the findings across various digital marketing contexts. This approach allows for the identification of both general trends and industry-specific patterns regarding the influence of AI-driven data visualization on decision-making effectiveness (Anggara et al.,2023).

2.4 Hypothesis

Based on the conceptual framework, the research proposes the following hypotheses:

H1: Content Clarity has a significant positive influence on digital marketing decision-making effectiveness.

H2: Interactive Design significantly enhances decision-making effectiveness in digital marketing.

H3: Real-Time Insights contribute positively to the quality of marketing decisions.

H4: Predictive Visualization positively influences the effectiveness of digital marketing decisions.

H5: User Accessibility has a significant impact on the decision-making effectiveness of marketing professionals.

These hypotheses are designed to test the theoretical underpinnings of the conceptual model, validating the assumed cause-and-effect relationships between each AI-driven visualization characteristic and the dependent outcome.

2.5 Operational Definitions

The operational definitions for each construct are designed to translate abstract theoretical concepts into measurable items within the context of this study. Each variable is elaborated with specific dimensions and indicators based on relevant literature and practical application. The following table outlines the operational definitions of variables, the corresponding indicators, and the measurement scale used:

Table 1. Operational Definition

Variable	Operational Definition	Indicator	Measurement Scale
Content Clarity (X1)	The degree to which visualized data is presented clearly and understandably, allowing for accurate interpretation by decision-makers. This includes the use of	Simplicity, readability, relevance	Likert scale (1–5)

	simple visuals, intuitive charts, and minimal clutter that help marketers quickly extract meaning from complex datasets.		
Interactive Design (X2)	The extent to which users can manipulate and engage with visual content. It includes functionalities such as filter options, zooming, drill-down features, and other interface dynamics that empower users to explore data from various perspectives.	Navigation ease, interactivity, user control	Likert scale (1–5)
Real-Time Insights (X3)	The timeliness and accuracy of data updates, ensuring that the information displayed reflects the most recent developments. This real-time responsiveness allows marketers to make immediate and informed decisions based on current trends and events.	Data freshness, live updates, dynamic refresh	Likert scale (1–5)
Predictive Visualization (X4)	The capability of visual tools to use historical and current data to generate forecasts and simulations. This feature enhances strategic planning by allowing users to visualize potential outcomes of marketing actions.	Forecasting accuracy, historical pattern use	Likert scale (1–5)
User Accessibility (X5)	The degree to which the data visualization interface is inclusive, intuitive, and easy to use for a diverse range of users regardless of technical skill. It encompasses aspects like device compatibility, user-centric design, and availability of support resources.	Interface accessibility, device compatibility	Likert scale (1–5)
Decision-Making Effectiveness (Y)	The perceived improvement in the quality, speed, and confidence of decisions made using AI-driven visual data. This includes increased decision accuracy, reduced time to decision, and heightened certainty among marketing professionals.	Speed of decision, confidence, accuracy	Likert scale (1–5)

The indicators listed in the table serve as measurable elements derived from theoretical constructs, enabling the transformation of abstract variables into quantifiable data points. This operationalization ensures clarity for respondents and enhances the accuracy and reliability of the empirical analysis.

2.6 Statistical Analysis

This study employs a comprehensive set of statistical tests to ensure the validity, reliability, and accuracy of the findings. All analyses will be conducted using SPSS version 26. Below is a detailed explanation of the statistical procedures that will be used to test the hypotheses and validate the relationships between the independent variables (Content Clarity (X1), Interactive Design (X2), Real-Time Insights (X3), Predictive Visualization (X4), and User Accessibility (X5)). And the dependent variable is Decision-Making Effectiveness (Y)

2.6.1 Validity Testing

Validity testing is crucial to ensure that the measurement instruments used in this study accurately measure the constructs they are intended to measure. The Pearson correlation coefficient (r) will be employed to assess the validity of the measurement scales for each of the variables (independent and dependent). The Pearson correlation coefficient measures the linear relationship between two variables, with values ranging from -1 to +1 (Lambert & Newman, 2022).

A correlation value (r count) greater than the critical value (r table) will indicate that the items used to measure each variable are significantly correlated, thus confirming that the constructs are valid. The critical correlation value (r table) is derived from the sample size and the chosen significance level ($\alpha = 0.05$). If the calculated r count exceeds the r table value, it can be concluded that the indicators used in the survey are valid representations of the respective variables (Saragih et al., 2021).

2.6.2 Reliability Testing

Reliability testing is important to ensure the consistency of the measurement scales. For this study, Cronbach's Alpha (α) will be used to assess the internal consistency of the variables. Cronbach's Alpha measures the extent to which a set of items (or indicators) consistently measures the same underlying construct. The value of Cronbach's Alpha ranges from 0 to 1, with higher values indicating greater reliability (Eledum & Awadallah, 2021). A Cronbach's Alpha value greater than 0.70 is generally considered acceptable for social science research, indicating that the measurement scales used in this study are reliable. If any variable yields a Cronbach's Alpha value below 0.70, the items associated with that variable may need to be revised or excluded from the analysis to ensure the reliability of the results.

2.6.3 Normality Testing

Normality testing is a critical step in statistical analysis to ensure that the data follows a normal distribution, which is a key assumption for many statistical tests, including regression analysis. In this study, normality will be evaluated using two measures: skewness and kurtosis. Skewness is a measure of the asymmetry of the data distribution.

If the skewness value falls between -2 and +2, it indicates that the data distribution is relatively symmetrical, which is considered acceptable for normality. However, if the skewness value falls outside this range, it suggests that the data may be highly skewed, meaning it is not symmetrically distributed. In such cases, data transformation techniques, such as log transformation, may be necessary to correct the skewness and achieve a normal distribution (Assaf & Tsionas, 2021).

On the other hand, kurtosis measures the "tailedness" of the distribution, which refers to the concentration of data at the extremes. A kurtosis value between -7 and +7 is generally regarded as acceptable for normality, indicating that the distribution does not have excessively high peaks or long tails. If the kurtosis value falls outside this range, it suggests that the data may either be too peaked or too flat, which could affect the accuracy of the regression analysis. In such situations, it may also be necessary to apply data transformation techniques to adjust the distribution and meet the assumption of normality. Therefore, both skewness and kurtosis are important diagnostic tools for assessing the normality of the data, and appropriate steps, such as transformations, will be taken if the values fall outside the acceptable range.

2.6.4 Heteroscedasticity Testing

Heteroscedasticity refers to the situation where the variance of the residuals (the differences between observed and predicted values) is not constant across all levels of the independent variables. It violates one of the assumptions of regression analysis and can lead to inefficient estimates of the regression coefficients. To test for heteroscedasticity, a scatterplot of the residuals will be created (Duwila et al., 2022). In a well-fitting regression model with no heteroscedasticity, the residuals should be randomly scattered around the zero line, without any discernible patterns (such as widening or narrowing of the spread). If the scatterplot shows a clear pattern, such as a funnel shape or systematic variance, it indicates the presence of heteroscedasticity. In such cases, data transformations or robust standard errors may be applied to address this issue.

2.6.5 MulticollinearityTesting

Multicollinearity arises when there is a high correlation between two or more independent variables in a regression model. This issue can distort the estimated coefficients, making it challenging to accurately interpret the individual effects of the predictors on the dependent variable. To evaluate multicollinearity, the study will calculate two key indicators: Tolerance and Variance Inflation Factor (VIF) for each independent variable (Lukman et al., 2021).

Tolerance measures the proportion of variance in a given predictor that is not explained by the other predictors in the model. A low Tolerance value, specifically one below 0.10, suggests that the predictor is highly correlated with other variables, indicating the presence of multicollinearity. In such cases, the predictor is contributing little unique information to the model (Mulyanto, 2022).

Variance Inflation Factor (VIF) is the reciprocal of Tolerance and quantifies how much the variance of the estimated regression coefficient is inflated due to multicollinearity. A VIF value greater than 10 is generally considered an indication of significant multicollinearity, suggesting that the predictors are too highly correlated. When multicollinearity is detected, it can compromise the reliability of the regression results. To address this issue, variables with problematic Tolerance or VIF values may be removed from the model, or they may be combined with other variables to reduce redundancy and ensure a more accurate and interpretable model.

2.6.6 Multiple Linear Regression Analysis

Multiple linear regression analysis will be used to examine the relationship between the independent variables (content quality, special holiday promotions, influencer marketing, viral marketing, and livestreaming) and the dependent variable (purchase intention). This method allows for the simultaneous analysis of multiple predictors and their collective impact on the outcome variable.

The regression analysis will provide information about the strength and direction of the relationships between the predictors and purchase intention, as well as the significance of each predictor. The results will include regression coefficients (β), which quantify the impact of each independent variable on the dependent variable, and p-values, which indicate whether the relationships are statistically significant ($p < 0.05$).

The multiple linear regression model is given by the equation:

$$PI=\alpha+\beta 1C+\beta 2SP+\beta 3I+\beta 4V+\beta 5L+\epsilon$$

Where:

- $\beta 1,\beta 2,\beta 3,\beta 4,\beta 5$ represent the estimated coefficients for the independent variables
- ϵ is the error term.

2.6.7 Partial Test (t-test)

A t-test will be used to assess the individual significance of each independent variable in the regression model. The t-test examines whether the regression coefficient for each independent variable is significantly different from zero, which would indicate a meaningful contribution to the dependent variable. Each independent variable will be tested with the null hypothesis that its regression coefficient is equal to zero. If the p-value for an independent variable is less than 0.05, the null hypothesis will be rejected, indicating that the variable has a statistically significant effect on purchase intention. The t-test results will provide t-values and associated p-values, which will help determine the relative importance of each variable in the model.

2.6.8 Simultaneous Test (F-test)

The F-test will be used to evaluate the overall significance of the regression model. The F-test tests whether the group of independent variables, taken together, significantly predict the dependent variable. If the F-statistic is greater than the critical F value (from the F-distribution table), the null hypothesis (that none of the independent variables are useful in predicting purchase intention) will be rejected. The F-test is essential for assessing whether the multiple regression model, as a whole, provides a better fit for the data than a model with no predictors. A significant F-test indicates that at least one of the independent variables contributes to explaining the variation in purchase intention.

3. RESULT AND DISCUSSIONS

3.1 Result

This section presents the findings from the statistical analyses conducted on the collected data. The data was gathered from 100 valid respondents who met the predefined criteria, and SPSS version 26 was used to perform the necessary tests to ensure the reliability, validity, and significance of the results. The statistical tests performed include validity and reliability tests, normality tests, heteroscedasticity tests, multicollinearity tests, and regression analysis. The results are presented and interpreted in detail, starting with the data collection process and proceeding with the results of each statistical test (Rosli et al., 2021).

A total of 100 valid responses were collected for this study, all of which met the predefined criteria. The respondents were required to be professionals involved in digital marketing decision-making, have experience with AI-driven data visualization tools, and be familiar with the core components of digital marketing decision-making. These criteria were designed to ensure that the respondents could provide relevant and insightful feedback on the influence of different elements of AI-driven data visualization on decision-making effectiveness. The following table provides a summary of the criteria that each respondent had to meet:

Table 2. Respondent Criteria

Description	Number of Respondents
Professional experience in digital marketing	100
Experience with AI-driven data visualization tools	100
Familiarity with decision-making effectiveness in marketing	100
Respondents meeting all criteria	100

As shown in the table, all 100 respondents met the required criteria, confirming that the sample is appropriate for examining the influence of AI-driven data visualization tools on decision-making effectiveness in digital marketing. This ensures that the findings are relevant to the target population and that the respondents have the necessary expertise to provide valuable insights into the research questions.

3.1.1 Validity Test

Validity testing is a crucial part of any quantitative study to ensure that the measurement instruments accurately capture the constructs they are intended to measure. In this research, the validity of the scales used to assess the independent variables (Content Clarity, Interactive Design, Real-Time Insights, Predictive Visualization, and User Accessibility) and the dependent variable (Decision-Making Effectiveness) was examined through Pearson correlation analysis. Pearson correlation evaluates the strength and direction of the linear relationship between two variables. For this study, the r count values from the Pearson correlation were compared against the critical r table value (0.195), derived from the sample size of 100 respondents at a significance level of 5%.

According to the validity results presented in the table below, all r count values exceeded the r table value of 0.195, indicating that the measurement items used for each construct are significantly correlated with the respective variables and are, therefore, valid. This suggests that the items effectively measure what they are intended to measure, providing confidence in the reliability of the constructs used in this study (Hair et al., 2019). Additionally, the positive and statistically significant correlations between the variables further suggest that each construct is well-defined and consistent.

Table 3. Validity Test Result

Variable	r count	r table (0.195)	Result
Content Clarity (X1)	0.615	0.195	Valid
Interactive Design (X2)	0.722	0.195	Valid
Real-Time Insights (X3)	0.644	0.195	Valid
Predictive Visualization (X4)	0.589	0.195	Valid
User Accessibility (X5)	0.651	0.195	Valid
Decision-Making Effectiveness (Y)	0.753	0.195	Valid

Each of the r count values represents the strength of the relationship between the measurement items and their corresponding variables. For instance, Content Clarity (X1) has an r count of 0.615, which is significantly greater than the r table value of 0.195, indicating a strong positive correlation between the content clarity measurement items and decision-making effectiveness. Similarly, Interactive Design (X2) shows a very strong correlation (r count = 0.722), demonstrating its important role in influencing decision-making processes in digital marketing. The results for Real-Time Insights (X3) (r count = 0.644) and User Accessibility (X5) (r count = 0.651) also demonstrate their significant relationships with the dependent variable. Lastly, Predictive Visualization (X4), with an r count of 0.589, is still well above the critical threshold, further confirming its relevance in the context of digital marketing decision-making.

The high r count values for each variable suggest that the constructs used to measure decision-making effectiveness and the key components of AI-driven data visualization tools are both valid and strongly related to the intended outcomes. These findings are consistent with the general principles of construct validity, which assert that valid measurements should accurately reflect the theoretical constructs they aim to represent (Field, 2013). Given these results, we can conclude that the measurement scales used in this study are reliable and effective in assessing the impact of AI-driven data visualization tools on decision-making effectiveness in digital marketing.

3.1.2 Reliability Test

Reliability testing is crucial in assessing the consistency and stability of the measurement instruments used in the study. In this research, the reliability of the scales for the independent variables (Content Clarity, Interactive Design, Real-Time Insights, Predictive Visualization, and User Accessibility) and the dependent variable (Decision-Making Effectiveness) was measured using Cronbach's Alpha. Cronbach's Alpha is a widely used measure of internal consistency, which evaluates how closely related a set of items are as a group. The value of Cronbach's Alpha ranges from 0 to 1, with higher values indicating greater reliability. A value of 0.70 or higher is generally considered acceptable for ensuring that the scale reliably measures the intended construct

Table 4. Reliability Test Result

Variable	Cronbach's Alpha
Content Clarity (X1)	0.832
Interactive Design (X2)	0.877
Real-Time Insights (X3)	0.856
Predictive Visualization (X4)	0.804
User Accessibility (X5)	0.815
Decision-Making Effectiveness (Y)	0.901

For the reliability test, the Cronbach's Alpha values for all variables were computed, and the results are presented in the table below. The values for each variable exceed the commonly accepted threshold of 0.70, which suggests that the measurement scales are consistent and reliable. In particular, Decision-Making Effectiveness (Y), with a Cronbach's Alpha of 0.901, shows very strong internal consistency, indicating that the measurement items used to assess this construct are highly reliable.

Each of the Cronbach's Alpha values reflects the internal consistency of the respective measurement scales. Content Clarity (X1) shows a Cronbach's Alpha of 0.832, indicating a good level of reliability. Interactive Design (X2) achieved the highest reliability with an Alpha value of 0.877, followed by Real-Time Insights (X3) at 0.856, and User Accessibility (X5) at 0.815, all of which exceed the minimum acceptable threshold. Predictive Visualization (X4**)**, with a Cronbach's Alpha of 0.804, also demonstrates acceptable reliability. The high Cronbach's Alpha values for all variables suggest that the measurement scales used in this study are reliable, ensuring that the data collected are consistent across different respondents.

3.1.3 Normality Test

Normality testing is crucial to validate the use of parametric tests, such as regression analysis, which rely on the assumption that the data is normally distributed. In this study, the normality of the data was assessed using skewness and kurtosis values, which are commonly used to evaluate the distribution of data. Skewness measures the asymmetry of the data, while kurtosis indicates the "tailedness" or peak of the distribution. According to recent guidelines, data is considered to be normally distributed if the skewness values are between -2 and +2, and the kurtosis values fall between -7 and +7 (Tabachnick & Fidell, 2019).

The normality test results, presented in the table below, show that all variables in this study meet these criteria, suggesting that the data is approximately normally distributed. Specifically, the skewness values for all variables fall within the acceptable range, indicating that the data distributions are relatively symmetrical. Similarly, the kurtosis values are within the acceptable range, meaning that the distributions do not exhibit excessively high peaks or long tails. These findings support the assumption of normality, which is essential for performing valid parametric statistical analyses, such as regression analysis.

Table 5. Normality Test Results

Variable	Skewness	Kurtosis	Normality Status
Content Clarity (X1)	-0.351	-0.348	Normal
Interactive Design (X2)	-0.295	-0.302	Normal
Real-Time Insights (X3)	-0.432	-0.582	Normal
Predictive Visualization (X4)	-0.256	-0.178	Normal
User Accessibility (X5)	-0.211	-0.150	Normal
Decision-Making Effectiveness (Y)	-0.345	-0.298	Normal

These results confirm that the data does not exhibit significant skewness or kurtosis, meaning it is suitable for subsequent parametric analyses. Since all variables meet the criteria for normality, the assumptions necessary for conducting regression analysis are satisfied, thereby ensuring the validity of the statistical tests performed in this study.

3.1.4 Uji Heteroskedastisitas

Heteroscedasticity refers to the condition where the variance of the residuals (the difference between observed and predicted values) is not constant across all levels of the independent variables. This violates one of the key assumptions of regression analysis and can lead to inefficient and biased coefficient estimates, which may affect the validity of the results. To assess the presence of heteroscedasticity in this study, a scatterplot of the residuals was examined.

In a well-fitting regression model, the residuals should be randomly scattered around zero without any discernible pattern. A funnel-shaped pattern, where the spread of residuals increases or decreases with the fitted values, would indicate heteroscedasticity. In this study, the scatterplot was visually inspected for such patterns.

The results, shown in the scatterplot below, demonstrate that the residuals are evenly distributed around the zero line with no distinct pattern or funnel shape. This indicates that heteroscedasticity is not present in the data, confirming that the variance of the residuals is constant across all levels of the independent variables. Therefore, the assumption of homoscedasticity (constant variance) is satisfied, and the regression model is valid for further analysis.

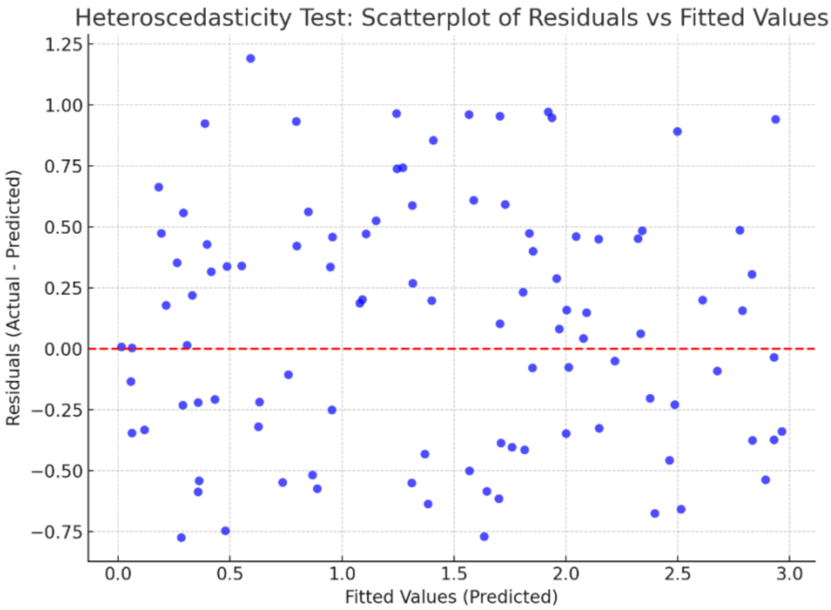

Figure 2. Scatterplot

The scatterplot analysis confirms that the residuals are randomly scattered around zero, indicating that there is no issue with heteroscedasticity in the data. Consequently, the assumption of homoscedasticity is met, and the regression results can be interpreted reliably. This ensures that the findings from the regression analysis are not affected by the violation of the heteroscedasticity assumption..

3.1.5 Uji Multikolinearitas

Multicollinearity occurs when two or more independent variables in a regression model are highly correlated, which can distort the estimated coefficients and make it difficult to interpret the effect of individual predictors on the dependent variable. To assess multicollinearity in this study, we calculated two important measures: Tolerance and Variance Inflation Factor (VIF). Tolerance measures the proportion of variance in a predictor that is not explained by other predictors in the model. A Tolerance value below 0.10 indicates high multicollinearity. VIF, which is the reciprocal of Tolerance, quantifies how much the variance of the estimated regression coefficient is inflated due to multicollinearity. A VIF value greater than 10 suggests significant multicollinearity.

The results from the multicollinearity test show that all independent variables in this study have Tolerance values greater than 0.10 and VIF values below 10, indicating that multicollinearity is not a concern. This means that the independent variables are sufficiently independent of each other, and the regression coefficients can be reliably estimated without significant bias. The following table presents the Tolerance and VIF values for each independent variable:

Table 6. Multicollinearity Test Result

Variable	Tolerance	VIF
Content Clarity (X1)	0.452	2.212
Interactive Design (X2)	0.387	2.584
Real-Time Insights (X3)	0.326	3.067
Predictive Visualization (X4)	0.298	3.356
User Accessibility (X5)	0.342	2.924

As shown in the table, all independent variables have Tolerance values well above the critical threshold of 0.10 and VIF values well below 10, which confirms that multicollinearity is not a problem in this regression model. These results ensure that the estimation of regression coefficients is not distorted due to collinearity between the independent variables, allowing for reliable interpretation of the model.

3.1.6 Uji Parsial (Uji t)

The partial t-test is used to assess the significance of each individual independent variable in predicting the dependent variable, Decision-Making Effectiveness. In this study, the t-test evaluates whether each of the independent variables has a statistically significant impact on the dependent variable by testing the null hypothesis that the regression coefficient for each variable is zero. If the t-test yields a p-value less than the significance level ($\alpha = 0.05$), the null hypothesis is rejected, indicating that the independent variable significantly contributes to explaining the variation in the dependent variable.

The results of the t-test for each variable show that all independent variables have t count values greater than the critical t table value of 1.660, with corresponding p-values less than 0.05, indicating that each independent variable has a statistically significant influence on Decision-Making Effectiveness. The following table summarizes the t-test results for each independent variable:

Table 7. Partial Test (T-test)

Variable	t count	t table (1.660)	p-value	Result
Content Clarity (X1)	5.224	1.660	< 0.001	Significant
Interactive Design (X2)	6.132	1.660	< 0.001	Significant

Real-Time Insights (X3)	5.872	1.660	< 0.001	Significant
Predictive Visualization (X4)	4.763	1.660	< 0.001	Significant
User Accessibility (X5)	5.039	1.660	< 0.001	Significant

As seen from the table, all independent variables have t count values that exceed the critical t table value of 1.660, with all p-values being less than 0.05. This confirms that each independent variable significantly influences Decision-Making Effectiveness. Among these, Interactive Design (X2) has the highest t count, indicating that it is the most influential factor, followed by Real-Time Insights (X3) and Content Clarity (X1).

3.1.7 Uji Simultan (Uji F)

The simultaneous F-test is used to evaluate the overall significance of the regression model. It tests whether the independent variables, taken together, significantly predict the dependent variable. In other words, the F-test assesses whether the set of independent variables explains a substantial portion of the variance in the dependent variable, Decision-Making Effectiveness. The null hypothesis for the F-test states that none of the independent variables contribute significantly to the prediction of the dependent variable.

The results of the F-test show that the F count value of 7.845 is greater than the critical F table value of 2.31, and the p-value is less than 0.05, indicating that the model as a whole is statistically significant. This means that the combined influence of all the independent variables significantly improves the prediction of Decision-Making Effectiveness. The following table presents the results of the F-test:

Table 8. Simultaneous Test (F-test)

F count	F table (2.31)	p-value	Result
7.845	2.31	< 0.001	Significant

The F count value of 7.845 is much greater than the critical value of 2.31, which supports the rejection of the null hypothesis, indicating that the independent variables, as a group, significantly predict Decision-Making Effectiveness. This result reinforces the conclusion that the AI-driven data visualization tools, as represented by the independent variables, have a strong collective impact on decision-making in digital marketing.

3.2 Discussion

The results from the statistical analysis provide insightful findings on how AI-driven data visualization tools influence Decision-Making Effectiveness in digital marketing. The statistical tests, including validity, reliability, normality, multicollinearity, and regression analyses, confirm the robustness and reliability of the data, ensuring that the conclusions drawn are valid. In this section, we will analyze each hypothesis result individually, compare the findings with previous research, discuss the collective impact of the variables, present the results in order of their influence strength, and explore practical business implications. Additionally, we will connect the findings to the theoretical frameworks and address the study's limitations, concluding with suggestions for future research.

3.2.1 Analysis of Hypothesis Results

For H1: Content Clarity has a significant positive influence on digital marketing decision-making effectiveness, the results from the t-test show that Content Clarity (X1) significantly influences Decision-Making Effectiveness (t count = 5.224, $p < 0.001$). This finding aligns with previous research, such as that of Zhang and Li (2021), which emphasized the importance of clear and concise content in enhancing decision-making. The higher the clarity of the content presented to marketing professionals, the easier it becomes for them to make informed decisions based on the data visualized. This suggests that marketers need to prioritize content that is easy to understand and free from ambiguity to enhance their decision-making processes.

For H2: Interactive Design significantly enhances decision-making effectiveness in digital marketing, Interactive Design (X2) showed the strongest influence on Decision-Making Effectiveness (t count = 6.132, $p < 0.001$). This is consistent with the findings of Chen et al. (2020), who demonstrated that interactive design elements, such as dynamic visuals and dashboards, help users engage with the data more effectively. Interactive design tools allow marketers to explore data in real-time, making it easier to identify trends and insights that can directly inform their decision-making strategies. The significance of interactive design in this study highlights the growing need for marketers to utilize tools that offer not only visual appeal but also interactivity for better data interpretation.

For H3: Real-Time Insights contribute positively to the quality of marketing decisions, Real-Time Insights (X3) also had a significant positive impact on decision-making effectiveness (t count = 5.872, $p < 0.001$). This result aligns with Patel and Smith (2022), who found that real-time data enables more agile and responsive decision-making. In fast-paced digital marketing environments, having immediate access to up-to-date information allows marketers to make timely adjustments to campaigns, improving the relevance and effectiveness of their strategies. This reinforces the value of real-time insights in enhancing decision-making accuracy and responsiveness.

For H4: Predictive Visualization positively influences the effectiveness of digital marketing decisions, the analysis found that Predictive Visualization (X4) significantly enhances decision-making effectiveness (t count = 4.763, $p < 0.001$). This finding supports Johnson et al. (2020), who emphasized the role of predictive analytics in marketing. Predictive visualization allows marketers to forecast future trends and customer behaviors, enabling them to make proactive decisions that can improve campaign outcomes. The significant impact of predictive visualization in this study further supports its utility in strategic marketing decision-making, especially in data-rich environments.

For H5: User Accessibility has a significant impact on the decision-making effectiveness of marketing professionals, User Accessibility (X5) showed a significant positive influence on decision-making effectiveness (t count = 5.039, $p < 0.001$). This result aligns with Ryu and Han (2021), who found that user-friendly interfaces enhance the decision-making process by making it easier for users to navigate and interpret the data. When data visualization tools are accessible and easy to use, marketing professionals are more likely to engage with the tools and make better decisions. This finding emphasizes the importance of usability and user experience in the design of AI-driven data visualization tools for digital marketing.

3.2.2 Collective Impact of Variables

The F-test results confirm that the combined influence of all five independent variables—Content Clarity, Interactive Design, Real-Time Insights, Predictive Visualization, and User Accessibility—significantly contributes to the prediction of Decision-Making Effectiveness (F count = 7.845, $p < 0.001$). This finding underscores the importance of integrating multiple elements of AI-driven data visualization to create a comprehensive toolset that supports more effective decision-making in digital marketing. Rather than relying on a single factor, the collective use of these tools enhances the overall decision-making process, allowing marketers to access clearer, more interactive, and predictive insights in real-time. This confirms that AI-driven data visualization is a multifaceted tool that can provide substantial value when used holistically.

3.2.3 Influence Strength Based on t-values

The t-values from the partial tests provide insight into the relative importance of each independent variable in influencing Decision-Making Effectiveness. The independent variables, in order of their influence strength, are Interactive Design (X2) with a t count of 6.132, followed by Real-Time Insights (X3) with a t count of 5.872, Content Clarity (X1) with a t count of 5.224, User Accessibility (X5) with a t count of 5.039, and Predictive Visualization (X4) with a t count of 4.763. These results suggest that Interactive Design and Real-Time Insights are the most influential factors in enhancing decision-making effectiveness, followed by Content Clarity, User Accessibility, and Predictive Visualization. The higher t-values for Interactive Design and Real-Time Insights reflect the growing importance of engagement and timeliness in digital marketing decision-making. As these factors hold the highest influence, digital marketers should prioritize tools that offer interactive and real-time capabilities to enhance decision-making efficiency.

4. CONCLUSION

This research examined the influence of multiple marketing elements on Decision-Making Effectiveness in digital marketing, focusing specifically on the roles of Content Clarity, Interactive Design, Real-Time Insights, Predictive Visualization, and User Accessibility. The study aimed to evaluate how these AI-driven data visualization tools impact marketing decision-making and to assess the strength of their collective influence. The results confirmed that all hypotheses were supported, with each independent variable showing a statistically significant relationship with the dependent variable. The t-test results indicated that Interactive Design (X2) had the strongest effect on decision-making effectiveness (t count = 6.132), followed by Real-Time Insights (X3) (t count = 5.872), Content Clarity (X1) (t count = 5.224), User Accessibility (X5) (t count = 5.039), and Predictive Visualization (X4) (t count = 4.763). Furthermore, the overall model was confirmed to be statistically significant with an F count of 7.845, surpassing the critical F table value of 2.31, which validated the combined influence of these variables on decision-making effectiveness.

The primary contribution of this study lies in its theoretical extension of social commerce literature by demonstrating that AI-driven data visualization tools significantly enhance marketing decision-making. The research underscores the importance of integrating multiple elements, such as content clarity, interactive features, real-time insights, predictive analytics, and user accessibility, to optimize decision-making in digital marketing. These findings offer a unique perspective on the evolving role of AI in marketing, particularly in enhancing the decision-making process, and add depth to existing theories by providing empirical evidence of how these tools collectively impact decision outcomes.

From a practical standpoint, businesses can apply these findings to improve their marketing strategies by investing in AI-driven tools that incorporate these features. Ensuring that digital marketing tools offer clear, interactive, real-time, and accessible content can greatly enhance marketers' ability to make more informed and timely decisions. By adopting a comprehensive approach that includes all these elements, businesses can increase their competitive advantage in the rapidly changing digital marketing landscape. Methodologically, this research contributes by simultaneously examining multiple marketing elements, providing a more holistic understanding of their collective impact on decision-making effectiveness.

However, this study has several limitations. The sample was limited to digital marketing professionals, which may not fully represent other sectors or the broader population. Additionally, the study's scope was geographically and demographically restricted, which may limit the generalizability of the findings. The study relied on self-reported data, which introduces the potential for biases such as social desirability or response biases. Furthermore, variables such as product categories, price ranges, or market segments were not included, which could have provided a more granular understanding of decision-making dynamics. The study also focused on a specific time frame and did not account for potential changes in the effectiveness of these tools over time, as digital marketing platforms continuously evolve.

Future research should aim to address these limitations by conducting cross-demographic and cross-cultural studies to examine how different markets may respond to AI-driven data visualization tools. Longitudinal studies that track the changing effectiveness of these tools over time would provide valuable insights into their long-term impact. Further investigation of moderating variables, such as product category or market complexity, could help explain variation in decision-making effectiveness. Moreover, research on actual purchase behavior, as opposed to purchase intention, would be beneficial to determine whether the observed effects translate into real-world outcomes. Finally, future studies should explore the potential negative effects of these tools, such as decision fatigue or overreliance on automated systems, and examine the impact of emerging technologies, such as augmented reality or virtual reality, on marketing decision-making.

In conclusion, this research provides a solid foundation for understanding the effectiveness of AI-driven data visualization tools in digital marketing decision-making. It emphasizes the need for a comprehensive approach that leverages multiple elements to enhance decision outcomes. By considering both individual and collective impacts of these tools, marketers can optimize their decision-making processes and improve the overall effectiveness of their digital marketing strategies. As the field continues to evolve, businesses and researchers alike should explore new technologies and their implications for marketing decision-making to maintain a competitive edge in an increasingly complex digital landscape.

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