

Streamlining Content Marketing: Antecedents of Productivity in the Age of AI Expansion

*Muhammad Syafi'i A Basalamah¹, Regina R.², Mursalim Laekkeng¹, Said Hasan¹ ¹ Department of Management, Universitas Muslim Indonesia, Indonesia ²Department of Management, Universitas Negeri Makassar, Indonesia

Citation (APA 7th): Basalamah, M. S. A., Regina, R., Laekkeng, M., & Hasan, S. (2025). Streamlining Content Marketing: Antecedents of Productivity in the Age of AI Expansion. *Jurnal Minds: Manajemen Ide Dan Inspirasi, 12*(1), 93–104. https://doi.org/10.24252/minds.v1 2i1.56310

Submitted: 27 Maret 2025 Revised: 10 June 2025 Accepted: 11 June 2025 Published: 22 June 2025



ABSTRACT: Artificial intelligence (AI) is transforming content production, influencing both quality and productivity in marketing teams. This study investigates the impact of AI utilization and content quality on the productivity of content marketing professionals in Indonesia. Using purposive sampling, data from 200 respondents were analyzed through structural equation modeling (SmartPLS 4). Findings reveal that Al significantly enhances content guality and directly improves team productivity. Content quality also contributes positively to productivity, though to a lesser extent. The study suggests that Al functions not only as a tool but as a creative collaborator, streamlining processes while supporting innovation. However, reliance on self-reported questionnaire data presents limitations, particularly concerning subjectivity and potential bias. This research offers one of the earliest empirical insights from Indonesia on the synergy between AI and human creativity in marketing, as emphasizing its managerial relevance for organizations seeking to optimize performance through intelligent systems.

Keywords: AI Utilization; Content Quality; Marketing Productivity; AI-Driven Tools; Content Creators

INTRODUCTION

The digital age has recently transformed how organizations promote their products and services (Ratna et al., 2024). The most significant development resulting from this trend is increased content marketing (Yoo et al., 2019). This marketing approach focuses on creating and disseminating valuable, relevant, and consistent information to attract and maintain a specific audience and ultimately foster profitable consumer activities (Güner Gültekin et al., 2024). Collaboration between content creators and companies, particularly in the e-commerce sector (Keni et al., 2024), is rapidly expanding in Indonesia. Companies such as Tokopedia, Shopee, and Bukalapak have been aggressively partnering with content creators, and service providers such as Grab and Gojek have been engaged in this partnership. As a result, content marketing creators, influencers, and key opinion leaders (KOLs) collaborate to enhance their reach (Gupta & Khan, 2024).

Moreover, content creators are crucial for establishing brand recognition, improving audience interaction, and shaping consumer purchase behaviors (Gupta & Khan, 2024). Data from We Are Social indicates that Indonesia ranks among the major markets in Southeast Asia, with a steadily rising internet penetration and over 77% of the population actively engaging with the internet (We Are Social, 2023). This indicates that as the number of individuals engaging with digital platforms increases (Elhajjar, 2024), content marketing has emerged as one of the most potent marketing instruments (Keni et al., 2024).

Nevertheless, content creators and enterprises encounter obstacles to swift advancement (Wood & Moss, 2024). The primary difficulty is using technology, especially artificial intelligence (AI), to enhance organizational efficiency and content management (Kim & Seo, 2023). Artificial Intelligence has become essential in multiple marketing facets (Alzebda & Matar, 2024), including consumer data management, automated content generation, and analytics for content personalization (Graeme et al., 2020). Despite the anticipated improvements in efficiency and effectiveness due to AI, a disparity persists between theoretical expectations and practical applications concerning AI's impact on productivity in content marketing (Güner Gültekin et al., 2024).

Indonesia is experiencing a notable rise in collaboration between content creators and corporations, mainly via social media platforms like Instagram, YouTube, and TikTok. Content marketers are frequently under pressure to consistently generate innovative, pertinent, and high-calibre content within tight timeframes (We Are Social, 2023). Conversely, corporations anticipate that the content produced will substantially influence sales and consumer engagement (Aljarah et al., 2024).

Numerous companies have begun employing AI technology to enhance content development processes and expedite marketing techniques (Chatterjee, 2020). AI is employed to collect consumer behavior data, customize the content, and evaluate the efficacy of campaigns (Chen et al., 2023). Although AI technology is becoming more popular, there is still a gap in understanding how it can enhance marketing team productivity and improve content quality (Santoro et al., 2024). Despite the extensive global discourse on the integration of AI in content marketing, research in Indonesia remains scarce (Alzebda & Matar, 2024). Previous research has predominantly concentrated on implementing AI in substantial areas such as finance and industry (Serge-Lopez et al., 2020).

However, little research has been done on how it affects the cooperation between corporations and content creators. Second, there is a conflict between the need to create content quickly to remain competitive in the market and the creation of excellent, audience-relevant content. Few studies have looked at the balance between these two factors in the context of Al use, while many have focused on a single feature (Kumar & Suthar, 2024). Third, the majority of recent studies still make a distinction between technological use and the human components of creativity. It is crucial to look at how Al and humans might collaborate to foster creativity and produce meaningful and productive content.

Although terms such as "antecedents," "productivity," and "streamlining" are frequently used in discussions of content marketing, their conceptual underpinnings are often loosely defined. This study defines "antecedents of productivity" as both technological (e.g., Al utilization) and strategic (e.g., campaign design), which influence team performance in measurable ways. By grounding these constructs in theoretical frameworks such as TAM and the input-output model,

this research aims to move beyond thematic generalities to offer a more structured, operational definition of productivity in AI-assisted marketing contexts.

THEORETICAL REVIEW

Utilization of Artificial Intelligence

Al utilization is derived from the foundational theory established by Davis et al. (1989) concerning the Technology Acceptance Model (TAM), which underpins the comprehension of technology adoption within organizations, including the application of artificial intelligence (AI) in content marketing (Yaqub et al., 2024). The Technology Acceptance Model (TAM) posits that two primary elements, specifically perceived usefulness and perceived ease of use, affect the adoption of technology by individuals and organizations (Yousafzai et al., 2007), which asserts that technologies considered advantageous will facilitate their acceptance among users (King & He, 2006).

In content marketing, AI automates processes, including content development, audience behavior analysis, and message tailoring (Chatterjee et al., 2021) investigated the role of AI technology in expediting decision-making and improving marketing efficiency through data utilization to tailor customer interactions and optimize engagement (Chatterjee, 2020). AI enables firms to analyze client data more efficiently and precisely, improving content quality and marketing efficacy (Haenlein et al., 2019). Additional studies demonstrated that AI significantly influences the efficacy of digital marketing techniques. Additional studies indicate that implementing AI in content management aids organizations in resource allocation and enhances the optimization of marketing campaigns via automation (Kaplan & Haenlein, 2019). Furthermore, the application of AI in audience behavior analysis enables marketers to gain deeper insights into client preferences and provide more pertinent content.

Content Quality

Content quality is a crucial element of the effectiveness of content marketing tactics. The Elaboration Likelihood Model (ELM), created by Petty in 1986 (J. Kitchen et al., 2014), elucidates that high-quality messages affect the audience's processing and response to information. This approach categorizes information processing into central and peripheral pathways (Eckert & Goldsby, 1997). Messages conveyed via the central channel generally exert a lasting influence due to their engagement in profound cognitive processing, whereas the peripheral route depends on superficial signals (J. Kitchen et al., 2014).

Consequently, pertinent, captivating, innovative materials or messages are essential for augmenting audience engagement. Well-personalized content generally garners greater audience engagement (Kaplan & Haenlein, 2019), enhancing the efficacy of marketing campaigns. Furthermore, Gimpel (2020) underscores the significance of content relevance in engaging an audience's attention. Content that resonates with audience interests is more likely to generate favourable responses through direct interactions, such as comments and shares, or subsequent actions, such as product acquisitions.

According to (Wood & Moss, 2024), the growing utilization of AI technology in content creation demonstrates that AI can provide material that corresponds with audience preferences, facilitating message personalization and accelerating production time. AI facilitates real-time assessment of content performance, enabling marketers to enhance their efforts swiftly. This aligns with 's (2020) perspective, which asserts that content quality must be exciting and pertinent to the audience's requirements and tastes.

Marketing Team Productivity

Wassily Leontief's input-output paradigm, established in 1936, underpins the correlation between input (AI and content) and output (Marketing Team Productivity) (Ailloni-Charas, 1993). This idea illustrates the optimization of technology input to achieve elevated production. The inputoutput model is an economic theory that explains the link between inputs and outputs within an economic system (Magrath, 1988). This theory is pertinent in assessing the productivity of marketing teams, wherein inputs like AI technology and content quality can augment output in terms of team productivity. The input-output model demonstrates that enhancements in efficiency in one area can directly influence output in other sectors.

Concerning Marketing Team productivity, a study by Paul and Mukhopadhyay (2022) determined that productivity may be assessed by the quantity of material generated, time efficiency, and success in meeting marketing objectives. By utilizing AI technologies, marketing teams can diminish manual labour, enabling a greater concentration of essential strategic endeavours (Good & Stone, 2000). Furthermore, marketing teams should prioritize content quality to improve the efficacy of marketing initiatives, as superior content typically yields increased audience engagement. This also underscores the correlation between content quality and productivity (Berlak et al., 2021), asserting that high-quality content enhances audience engagement and enables marketing teams to accomplish their objectives more efficiently. Relevant, engaging, and original content fosters greater audience involvement, enhancing the ROI of marketing campaigns (Chevalier-Roignant et al., 2013). The application of AI in content generation and dissemination aids marketing teams in generating material more rapidly and efficiently while preserving high quality (Gupta & Khan, 2024).

In this study, antecedents of productivity are categorized into two main domains: (1) Technological antecedents, referring to Al-driven tools that enhance content production and personalization; and (2) Strategic antecedents, such as content design decisions that reflect human creativity and intent. These antecedents were selected based on their prevalence in Al-integrated marketing systems and their measurable impact on content quality and team performance.

According to the literature cited above, marketing teams' productivity is greatly impacted using AI and high-quality content. While content quality is the main factor influencing audience engagement, AI plays a crucial role in increasing these teams' productivity and personalizing material. Businesses can use AI to increase the effectiveness of their marketing teams while ensuring that the material produced is relevant and interesting to the target audience.

To ensure contemporary relevance, this study incorporates recent literature (post-2020) on generative AI, such as its integration into CRM systems (Chatterjee et al., 2021), AI-powered growth hacking strategies (Santoro et al., 2024), and adaptive content personalization (Chen et al., 2023). Earlier references, such as Berman (2012), have been contextualized historically, but the primary theoretical development now reflects recent advancements in AI-assisted marketing. This research suggests various hypotheses based on these foundations.

H1: AI Utilization significantly enhances Content Quality by personalizing and automating the content generation process.

H2: AI Utilization significantly enhances Marketing Team Productivity by diminishing manual tasks and augmenting time efficiency.

H3: Content Quality positively influences the marketing team's productivity; superior content enhances team performance by fostering increased audience engagement through relevant and compelling material.

RESEARCH METHOD

Research Design

This study employed a quantitative approach that utilized a cross-sectional survey design (Wang & Cheng, 2020). A cross-sectional approach was selected due to its efficiency in capturing data at a single point in time, allowing researchers to evaluate variable interdependencies without requiring longitudinal tracking. Such a design is particularly useful when assessing behavioral or perceptual constructs influenced by rapidly evolving technologies such as AI.

The choice of methodology aligns with the objective of this study: to assess current conditions in content marketing environments shaped by AI adoption. By capturing insights from a defined population of content creators, the design supports the identification of immediate trends and associations among constructs. The use of structural equation modeling (SEM) further enhances the analytical depth, enabling the examination of both direct and indirect effects within a theoretically grounded framework.

This approach is especially appropriate for investigating productivity determinants in dynamic, creative roles where technological tools increasingly mediate performance outcomes. Given the industry's pace of change, a cross-sectional survey allows for timely assessment while balancing feasibility and generalizability. While acknowledging its limitations in capturing causality, this method remains a valid and effective choice for mapping relationships between AI integration and team-level performance in the Indonesian marketing sector.

The constructs used in this model were selected based on both theoretical significance and prior empirical validation. Items measuring AI utilization and content quality were adapted from validated scales used by Kim & Seo (2023) and Katasonov et al. (2006). The operationalization of productivity aligns with prior studies on digital team performance (Berlak et al., 2021; Paul & Mukhopadhyay, 2022). This enhances the empirical integrity of the conceptual framework proposed.

Population and Sample

The population of this study is composed of marketing content creators currently operating in multiple cities throughout Indonesia. The rationale for this selection was the growing number of content marketing practitioners in Indonesia's main cities (Makassar, Surabaya, and Jakarta). Content creators are individuals or teams responsible for developing and supervising digital platforms. The purposive sampling technique (Robinson & Robinson, 2016) was employed to select a sample of 200 respondents, guaranteeing that only those with pertinent experience and knowledge would be included (Robinson & Robinson, 2016). This selection aimed to improve the reliability of the research findings.

Data Collection

The questionnaire was divided into several sections. The initial section pertains to demographic data intended to accumulate information on age, gender, education, and experience in content marketing. Second, a questionnaire was developed to evaluate the three primary variables. In the context of AI utilization, the assessment of the utilization of AI-based instruments in the content-creation process (Kim & Seo, 2023). Content Quality is evaluated for originality, visual appeal, relevance, and audience engagement (Katasonov et al., 2006). Finally, we assessed the marketing team's productivity by assessing the volume of content produced, time efficiency, team performance, and burden reduction due to AI technology (Good & Stone, 2000). We will then disseminate the questionnaire online using various platforms, including SurveyMonkey and Google Forms. The purpose of the research was disclosed to the respondents, and their data confidentiality was ensured to encourage their participation.

Data Analysis

Structural equation Modelling (SEM) was employed to analyze the collected data following the completion of the data collection phase with the support of SMART PLS 4.0. SEM is a statistical analysis technique that enables researchers to evaluate relationships between variables in a complex model (Sarstedt et al., 2021). However, the questionnaire will be evaluated for validity and reliability before conducting SEM analysis using Cronbach's alpha and confirmatory factor analysis (CFA). Reliability evaluates the consistency of the measurement results, whereas validity evaluates the instrument's ability to measure its intended function (Sharma et al., 2023). After the model has been tested and evaluated, the established hypothesis is examined to ascertain whether there is a substantial impact of AI Utilization and Content Quality on Marketing Team Productivity. The analysis results are interpreted to ascertain the impact of AI Utilization and Content Quality on the productivity of the Marketing Team.

The relevance and contribution of this research to the existing knowledge in the field of content marketing will be evaluated by comparing this finding with existing literature. In other words, this research method offers a systematic quantitative approach that provides a comprehensive understanding of the relationship between the use of AI, content quality, and the marketing team's productivity. Additionally, this study is anticipated to offer valuable suggestions for content marketing strategies in the digital age.

RESULTS

This study employed Loading Factor (LF), Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (CA) to examine the validity and reliability of the constructs. The analysis results indicated that all constructs possess satisfactory values, as presented in Table 1.

Table 1. Computation of LF, AVE, CR, CA							
Construct/Items	Loading Factor	AVE	CR	CA	VIF		
AI Utilization (AIU)		0.647	0.878	0.811			
AIU1 (AI Content Tools)	0.854				2.143		
AIU2 (AI Audience Analytics)	0.883				2.332		
AIU3 (AI Message Customization)	0.834				1.994		
AIU4 (Chatbot Integration)	0.614				1.263		
Content Quality (CQ)		0.689	0.898	0.856			
CQ1 (Content Relevance)	0.908				3.578		
CQ2 (Visual Appeal)	0.808				4.765		
CQ3 (Content Originality)	0.866				3.366		
CQ4 (Audience Engagement)	0.727				4.252		
Marketing Team Productivity (MTP)		0.694	0.895	0.829			
MTP1 (Content Volume)	0.437				1.09		
MTP2 (Time Efficiency)	0.929				3.871		
MTP3 (Team Performance)	0.933				4.271		
MTP4 (Workload Reduction)	0.924				4.022		

Al Utilization is a construction that quantifies the extent to which artificial intelligence (Al) technology is employed in the content marketing process. Four primary indicators comprise this construction: AlU1 is an indicator that quantifies the utilization of Al-based tools in the production of content. This indicator is significantly associated with the Al Utilization construct, as evidenced by its LF value of 0.854. AlU2: this indicator assesses Al's capacity to analyze audience data, with an LF value of 0.883, suggesting a substantial contribution to the Al Utilization construct. The AlU3 LF value of 0.834 indicates a strong correlation, as it measures how Al is employed to customize messages based on audience preferences. AlU4 measures the use of Al-based chatbots for audience interaction. Despite its lower LF value of 0.614, this indicator remains legitimate; however, it exhibits a weaker correlation than other indicators. The AVE value of 0.878 and CR of 0.811 suggest the Al construct's validity and reliability. An AVE value exceeding 0.50 indicates that this model can account for the majority of the variance in the indicators.

Subsequently, the variable content quality assesses the quality of content generated by marketers, emphasizing audience engagement, originality, visual attractiveness, and relevance. Additionally, this construct comprises four primary indicators. CQ1 has a loading value of 0.908, which suggests that it is highly effective in assessing the quality of content. The visual appeal of the content is measured by CQ2, which has an LF value of 0.808 and is also significantly correlated with content quality. The LF value of 0.866, which indicates a significant contribution to this construct, is used by CQ3 to evaluate the degree to which the content is deemed original. CQ4, which has an LF value of 0.727, is also a significant factor in evaluating content quality. In general, the AVE value for this construct is 0.689, and the CR is 0.898, suggesting that the content quality, as measured by these indicators, has excellent convergent validity and reliability. It is crucial to capture the audience's interest and improve their engagement with the content generated.

Marketing Team Productivity: this construct assesses the marketing team's efficacy in content generation, emphasizing workload reduction, content volume, time efficiency, and team performance. Four primary indicators comprise this variable. When MTP1 has an LF value of 0.437, it exhibits a lower correlation than the other indicators. The marketing team's productivity is significantly enhanced by MTP2, as evidenced by its exceptionally high LF value of 0.929. MTP3, with an LF value of 0.933, indicates that the team's productivity significantly impacts their performance. MTP4 quantifies the extent to which technology alleviates the manual workload. Additionally, this indicator boasts an impressive LF value of 0.924. Furthermore, the AVE value

of 0.694 and CR of 0.895 attest to the construct's high reliability and validity. Overall, the construct has good convergent validity, as indicated by the AVE value above 0.50, and the CR and Cronbach Alpha values above 0.70 demonstrate good reliability for all the constructs measured. Consequently, this construct can be employed to evaluate the relationships within the structural model.

Discriminant validity testing was performed to guarantee that each construct was distinct. The results of this test indicated that each construct had higher values for its indicators than for the indicators of other constructs, as evidenced by the correlation values between the indicators of each construct. Table 2 shows the results of the discriminant validity test, demonstrating that all constructs satisfy the criteria for adequate discriminant validity.

Table 2. Discriminant validity test						
Items	AIU	CQ	MTP			
AIU1	0.854	0.743	0.787			
AIU2	0.883	0.778	0.83			
AIU3	0.834	0.717	0.765			
AIU4	0.618	0.571	0.543			
CQ1	0.922	0.908	0.88			
CQ2	0.552	0.808	0.595			
CQ3	0.824	0.866	0.852			
CQ4	0.486	0.727	0.486			
MTP1	0.393	0.498	0.437			
MTP2	0.913	0.809	0.929			
MTP3	0.836	0.797	0.933			
MTP4	0.813	0.795	0.924			

These findings are consistent with prior research demonstrating that each construct is substantially distinct. Consequently, discriminant validity was satisfied, enabling the use of these constructs in additional model testing. Al Utilization, Content Quality, and Marketing Team Productivity correlate with their respective indicators. As an illustration, AlU1 exhibits the highest correlation value of 0.854, which is considerably more significant than its correlation with Content Quality (0.743) and Marketing Team Productivity (0.787). This is also relevant to the constructs of Content Quality and Marketing Team Productivity, in which the indicators of each construct exhibit a stronger correlation with their original constructs. This finding affirms that each construct in this research model has strong discriminant validity, indicating that the constructs accurately assess distinct characteristics.

Various concepts (AI Utilization, Content Quality, and Marketing Team Productivity) can be guaranteed to measure distinct variables that do not coincide with the assistance of strong discriminant validity. This is significant because it demonstrates that the variables can be clearly distinguished in the structural model, ensuring the relationship analysis results are valid and accurate. The validity of this discriminant provides a robust foundation for evaluating the causal relationship between AI Utilization, Content Quality, and Marketing Team Productivity. The Variance Inflation Factor (VIF) calculations used to identify multicollinearity issues in the research model are depicted in the table above, as indicated in Table 3. The high correlation between two independent variables in the model causes multicollinearity, leading to challenges in interpreting the regression results.

The general norm in VIF evaluation is that a value below 5 indicates the absence of significant multicollinearity. The variable CQ2 (Visual Appeal) had the highest recorded VIF value at 4.765, as indicated by the results in Table 1. Many of the variables in this model had relatively low VIF values. This suggests multicollinearity in this model is within permissible limits, as no VIF values exceed the threshold of 5 despite numerous correlating variables. Consequently, it can be inferred that this model has no significant multicollinearity issues, and the analysis can be conducted with precision without interference from correlation issues among the independent variables.

The results of the ensuing testing, which utilized structural equation modelling (SEM), suggest that the utilization of AI had a substantial positive impact on the productivity of the

marketing team and the quality of the content. Additionally, Table 4 illustrates that Content Quality positively affects Marketing Team Productivity.

Table 3. Path coefficient, Total Effects, and indirect effect						
Paths	Path coefficients	Total effects	Indirect effect			
AI Utilization -> Content Quality	0.879	0.879				
AI Utilization -> Marketing Team Productvt.	0.632	0.920	0.288			
Content Quality -> Marketing Team Prod.	0.328	0.328				

Table 3. Path coefficient, Total Effects, and Indirect effect

The SEM analysis assessed the influence of AI utilization and content quality on the marketing team productivity. The results suggest that adopting AI is critical for improving content quality, as evidenced by the significant direct effect on content quality, with a path coefficient of 0.879. AI is instrumental in personalizing and automating content creation to enhance quality. Furthermore, the path coefficient of 0.632 indicates that AI can significantly enhance a marketing team's productivity by automating processes and reducing workload.

Additionally, content quality (CQ) positively influences Marketing Team Productivity (MTP), as evidenced by a path coefficient of 0.328. This suggests that content quality improves team performance by increasing audience interaction enhancing the marketing team's effectiveness. Based on these findings, it is evident that AI utilization has a direct impact on the marketing team's productivity as well as an indirect influence through the enhancement of content quality. AI utilization improves content quality, affecting the marketing team's productivity, as evidenced by the indirect influence of 0.288.

DISCUSSION

The productivity of the content marketing team in Indonesia, particularly among content creators, has been substantially enhanced by using artificial intelligence (AI). AI facilitates the content creation process by automating it and enables higher levels of audience personalization. These findings confirm prior research that asserts AI's capacity to analyze audience behavior data, thereby enhancing the relevance and interest of the generated content for consumers. Collaboration between artificial intelligence (AI) and content creators has benefited consumer engagement in Indonesia's digital marketing sector, particularly in e-commerce.

Additionally, the efficacy of marketing campaigns has been demonstrated to be significantly enhanced by the quality of the content. This study discovered that audience engagement can be enhanced through the use of content that is original, pertinent, and visually appealing. This engagement can be measured regarding shares, likes, and comments (Ghesh et al., 2024). This is consistent with the current body of research, which indicates that audiences' information processing is influenced by high-quality content, thereby increasing the likelihood of conversion (Lin et al., 2023). The quality of content propelled by AI technology is critical in fostering consumer loyalty and influencing purchase decisions in a digitally competitive environment (Lee et al., 2020).

Also, the research substantiates that marketing teams experience a substantial increase in productivity when they can integrate AI technology with high-quality content. The reduction in manual burden and the time required to produce content indicate increased productivity. AI enables teams to concentrate more on innovative strategies to enhance audience engagement. These results corroborate prior research, which demonstrated that optimizing marketing team performance can be achieved through implementing technology, reducing routine tasks and creating more innovation opportunities (Alzebda & Matar, 2024).

The automation of numerous aspects of content production, including script creation and audience behavior analysis, has been demonstrated through AI in content marketing. Despite this, human creativity remains crucial in preserving the originality, relevance, and affective engagement of the generated content (Peltier et al., 2024). AI can produce data-relevant content; however, human creativity must incorporate cultural characteristics, social values, and more profound narratives.

Previous research has also demonstrated that AI can enhance productivity by processing data more quickly and accurately (Chopra et al., 2024). However, the content produced without human intervention has less emotive and personal appeal. Other research has also demonstrated that AI and humans can work together in a hybrid model (Mohammed, 2019). In this model, AI

assists in expediting repetitive tasks, while humans are responsible for marketing campaigns' creative and innovative aspects.

Additionally, the collaboration of AI and humans expedites the content creation process, which also allows creative teams to concentrate on innovation. This is consistent with prior research, which has demonstrated that AI in marketing enables teams to allocate less time to routine tasks, such as data collection and analysis, and to concentrate on innovative strategies that can enhance audience engagement (Santoro et al., 2024). Consequently, the focus of this collaboration is not solely on efficiency but also on how AI enables humans to realize their full creative potential. Also, The concept of content fatigue is increasingly relevant as digital consumers are inundated with high-frequency content. While AI streamlines content creation, it may also accelerate audience burnout due to overexposure. Future research should explore whether AI intensifies or mitigates content fatigue by examining engagement decline patterns and saturation points. Initial indicators suggest that while personalization reduces irrelevance, it does not necessarily alleviate emotional or cognitive fatigue in users.

CONCLUSION AND FURTHER STUDY

Although the context of this research is Indonesian, it is crucial to broaden the discussion to encompass other regions, mainly because the adoption of AI in content marketing varies substantially across different regions. AI has been more extensively and thoroughly integrated into various sectors, including marketing, in developed countries like the United States and Western Europe. In these countries, AI is employed to generate more intricate interactive experiences with audiences, in addition to content personalization, according to a study conducted by (Chatterjee et al., 2021); for instance, the utilization of artificial intelligence (AI) in virtual reality (VR) and augmented reality (AR) has emerged as a trend in marketing campaigns that are designed to offer consumers a more immersive experience.

In contrast, the content marketing sector in developing countries, including Indonesia, Philippines, and India, is still in the early phases of AI adoption. Diverse levels of technological infrastructure and digital literacy pose significant obstacles to the mainstream adoption of AI. However, the potential for development is substantial, particularly in light of the region's growing use of social media and the internet. Consequently, to offer a more comprehensive perspective, future research should investigate the impact of technological adoption disparities in these regions on content marketing strategies and the collaboration between humans and artificial intelligence (AI).

In conclusion, it is crucial to investigate the relationship between AI and human creativity, as well as the expansion of geographical context, to comprehend how AI can be adopted and optimized in various regions. Additional research that encompasses a broader sector and region will offer a more comprehensive understanding of the role of AI in enhancing content marketing productivity on a global scale.

It is important to consider the many limitations of this study. First, the study's very small sample size—200 respondents (content marketing providers) from various major Indonesian cities—restricts the findings' applicability to a larger population, especially in other sectors. Second, the use of online surveys as an instrument for gathering data may bring potential biases such respondent subjectivity and social desirability bias, which could affect the accuracy of the data obtained. Additionally, this study only used a quantitative methodology, which prevented it from thoroughly examining the dynamics of human-AI collaboration. Finally, applying these results to a broader context beyond Indonesia is restricted because the level of technology adoption in Indonesia may differ from that of other countries.

However, this study offers both theoretical and practical implications. Theoretically, this study contributes to the literature on adopting AI in content marketing in Indonesia, which has been previously entirely restricted. This study also presents opportunities for additional research on the impact of AI in other sectors and the collaboration between technology and human creativity. This study can serve as a foundation for future research on technology-based marketing strategies by investigating how AI enhances productivity through automation and analytics.

Practically, this study offers companies, particularly those in the e-commerce and content creation sectors, advice on effectively optimizing the use of AI in the marketing process. By

utilizing AI, companies can improve team productivity and expedite the content creation process without sacrificing quality. This is of paramount importance in a competitive business environment, where the success of digital marketing is contingent upon the quickness and relevance of content.

ETHICAL DISCLOSURE

All participants provided written informed consent prior to participation. They were informed about the study's purpose, their voluntary participation, the right to withdraw at any time, and the confidentiality of their responses.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest regarding the publication of this paper. Ethical approval was secured, and the research followed non-invasive methods, ensuring no harm or risk to the participants involved. This research received no specific grant from funding agencies in the public, commercial, or institutions. The authors declare that no competing financial or non-financial interests could be perceived as influencing the research reported in this article.

REFERENCES

- Ailloni-Charas, D. (1993). The Pursuit of Marketing Productivity. *Journal of Product & Brand Management*, *2*(3), 44–48. https://doi.org/10.1108/10610429310046698
- Aljarah, A., Ibrahim, B., & López, M. (2024). In AI, we do not trust! The nexus between awareness of falsity in AI-generated CSR ads and online brand engagement. *Internet Research, ahead-of-p*(ahead-of-print). https://doi.org/10.1108/INTR-12-2023-1156
- Alzebda, S., & Matar, M. A. I. (2024). Factors affecting citizen intention toward AI acceptance and adoption: the moderating role of government regulations. *Competitiveness Review: An International Business Journal, ahead-of-p*(ahead-of-print). https://doi.org/10.1108/CR-06-2023-0144
- Berlak, J., Hafner, S., & Kuppelwieser, V. G. (2021). Digitalization impacts productivity: a modelbased approach and evaluation in Germany's building construction industry. *Production Planning & Control, 32*(4), 335–345. https://doi.org/10.1080/09537287.2020.1740815
- Chatterjee, S. (2020). Al strategy of India: policy framework, adoption challenges and actions for government. *Transforming Government: People, Process and Policy, 14*(5), 757–775. https://doi.org/10.1108/TG-05-2019-0031
- Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A., & Ghosh, S. K. (2021). Adoption of artificial intelligence-integrated CRM systems in agile organizations in India. *Technological Forecasting and Social Change*, *168*(April), 120783. https://doi.org/10.1016/j.techfore.2021.120783
- Chen, Q., Yin, C., & Gong, Y. (2023). Would an AI chatbot persuade you: an empirical answer from the elaboration likelihood model. *Information Technology & People, ahead-of-p*(ahead-of-print). https://doi.org/10.1108/ITP-10-2021-0764
- Chevalier-Roignant, B., Trigeorgis, L., Chevalier-Roignant, B., & Trigeorgis, L. (2013). Strategic Management and Competitive Advantage. *Competitive Strategy*, *9780133129304*, 47–74. https://doi.org/10.7551/mitpress/9780262015998.003.0002
- Chopra, R., Bhardwaj, S., Thaichon, P., & Nair, K. (2024). Unpacking service failures in artificial intelligence: future research directions. *Asia Pacific Journal of Marketing and Logistics*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/APJML-03-2024-0393
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982
- Eckert, J. A., & Goldsby, T. J. (1997). Using the elaboration likelihood model to guide customer service-based segmentation. *International Journal of Physical Distribution & Logistics Management*, 27(9/10), 600–615. https://doi.org/10.1108/09600039710188657
- Elhajjar, S. (2024). Unveiling the marketer's lens: exploring experiences and perspectives on Al integration in marketing strategies. *Asia Pacific Journal of Marketing and Logistics, ahead*-

of-p(ahead-of-print). https://doi.org/10.1108/APJML-04-2024-0485

- Ghesh, N., Alexander, M., & Davis, A. (2024). The artificial intelligence-enabled customer experience in tourism: a systematic literature review. *Tourism Review*, *79*(5), 1017–1037. https://doi.org/10.1108/TR-04-2023-0255
- Good, D. J., & Stone, R. W. (2000). The impact of computerization on marketing performance . *Journal of Business & Industrial Marketing*, *15*(1), 34–56. https://doi.org/10.1108/08858620010311548
- Graeme, M., Kofi, O.-F., Alan, W., & Valentina, P. (2020). How live chat assistants drive travel consumers' attitudes, trust and purchase intentions: The role of human touch. *International Journal of Contemporary Hospitality Management*, *32*(5), 1795–1812. https://doi.org/10.1108/IJCHM-07-2019-0605
- Güner Gültekin, D., Pinarbasi, F., Yazici, M., & Adiguzel, Z. (2024). Commercialization of artificial intelligence: a research on entrepreneurial companies with challenges and opportunities. *Business Process Management Journal, ahead-of-p*(ahead-of-print). https://doi.org/10.1108/BPMJ-10-2023-0836
- Gupta, Y., & Khan, F. M. (2024). Role of artificial intelligence in customer engagement: a systematic review and future research directions. *Journal of Modelling in Management*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/JM2-01-2023-0016
- Haenlein, M., Kaplan, A., Tan, C. W., & Zhang, P. (2019). Artificial intelligence (AI) and management analytics. *Journal of Management Analytics*, 6(4), 341–343. https://doi.org/10.1080/23270012.2019.1699876
- J. Kitchen, P., Kerr, G., E. Schultz, D., McColl, R., & Pals, H. (2014). The elaboration likelihood model: review, critique and research agenda. *European Journal of Marketing*, 48(11/12), 2033–2050. https://doi.org/10.1108/EJM-12-2011-0776
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004
- Katasonov, A., Veijalainen, J., & Sakkinen, M. (2006). Content quality assessment and acceptance testing in location-based services. *International Journal of Pervasive Computing and Communications*, 2(1), 15–34. https://doi.org/10.1108/17427370780000138
- Keni, K., Wilson, N., & Teoh, A. P. (2024). Antecedents of viewers' watch behavior toward YouTube videos: evidence from the most populous Muslim-majority country. *Journal of Islamic Marketing*, 15(2), 446–469. https://doi.org/10.1108/JIMA-01-2023-0008
- Kim, J.-S., & Seo, D. (2023). Foresight and strategic decision-making framework from artificial intelligence technology development to utilization activities in small-and-medium-sized enterprises. *Foresight*, 25(6), 769–787. https://doi.org/10.1108/FS-06-2022-0069
- King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information and Management*, 43(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003
- Kumar, D., & Suthar, N. (2024). Ethical and legal challenges of AI in marketing: an exploration of solutions. *Journal of Information, Communication and Ethics in Society*, *22*(1), 124–144. https://doi.org/10.1108/JICES-05-2023-0068
- Lee, M., Lee, S. A., Jeong, M., & Oh, H. (2020). Quality of virtual reality and its impacts on behavioral intention. *International Journal of Hospitality Management*, *90*, 102595. https://doi.org/10.1016/J.IJHM.2020.102595
- Lin, F., Tian, H., Zhao, J., & Chi, M. (2023). Reward or punish: investigating output controls and content generation in the multi-sided platform context. *Internet Research*, 33(2), 578–605. https://doi.org/10.1108/INTR-05-2021-0292
- Magrath, A. J. (1988). People Productivity: Marketing's Most Valuable Asset. *Journal of Business Strategy*, *9*(4), 12–14. https://doi.org/10.1108/eb039235
- Mohammed, A. A. (2019). Using hybrid SEM artificial intelligence: Approach to examine the nexus between boreout, generation, career, life and job satisfaction. *Personnel Review*, *49*(1), 67–86. https://doi.org/10.1108/PR-06-2017-0180
- Peltier, J. W., Dahl, A. J., & Schibrowsky, J. A. (2024). Artificial intelligence in interactive marketing: a conceptual framework and research agenda. *Journal of Research in Interactive Marketing*, 18(1), 54–90. https://doi.org/10.1108/JRIM-01-2023-0030
- Ratna, S., Saide, S., Putri, A. M., Indrajit, R. E., & Muwardi, D. (2024). Digital transformation in

tourism and hospitality industry: a literature review of blockchain, financial technology, and knowledge management. *EuroMed Journal of Business*, *19*(1), 84–112. https://doi.org/10.1108/EMJB-04-2023-0118

- Robinson, O. C., & Robinson, O. C. (2016). Qualitative Research in Psychology Sampling in Interview-Based Qualitative Research : A Theoretical and Practical Guide A Theoretical and Practical Guide. *Qualitative Research in Psychology, in Press, 0887*(February), 1–25.
- Santoro, G., Jabeen, F., Kliestik, T., & Bresciani, S. (2024). Al-powered growth hacking: benefits, challenges and pathways. *Management Decision*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/MD-10-2023-1964
- Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial Least Squares Structural Equation Modeling. *Handbook of Market Research*, 1–47. https://doi.org/10.1007/978-3-319-05542-8_15-2
- Serge-Lopez, W.-T., Samuel, F. W., Robert, K. K. J., & Emmanuel, T. W. C. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. In *Business Process Management Journal: Vol. ahead-of-p* (Issue ahead-of-print). https://doi.org/10.1108/BPMJ-10-2019-0411
- Sharma, P. N., Liengaard, B. D., Hair, J. F., Sarstedt, M., & Ringle, C. M. (2023). Predictive model assessment and selection in composite-based modelling using PLS-SEM: extensions and guidelines for using CVPAT. *European Journal of Marketing*, *57*(6), 1662–1677. https://doi.org/10.1108/EJM-08-2020-0636
- Wang, X., & Cheng, Z. (2020). Cross-Sectional Studies: Strengths, Weaknesses, and Recommendations. *Chest*, *158*(1), S65–S71. https://doi.org/10.1016/j.chest.2020.03.012
- We Are Social. (2023). Digital 2023 Indonesia. *We Are Social*, 125. https://wearesocial.com/wp-content/uploads/2023/03/Digital-2023-Indonesia.pdf
- Wood, D., & Moss, S. H. (2024). Evaluating the impact of students' generative AI use in educational contexts. *Journal of Research in Innovative Teaching and Learning*, 17(2), 152– 167. https://doi.org/10.1108/JRIT-06-2024-0151
- Yaqub, M. Z., Badghish, S., Yaqub, R. M. S., Ali, I., & Ali, N. S. (2024). Integrating and extending the SOR model, TAM and the UTAUT to assess M-commerce adoption during COVID times. *Journal of Economic and Administrative Sciences, ahead-of-p*(ahead-of-print). https://doi.org/10.1108/JEAS-09-2023-0259
- Yoo, B., Katsumata, S., & Ichikohji, T. (2019). The impact of customer orientation on the quantity and quality of user-generated content. *Asia Pacific Journal of Marketing and Logistics*, 31(2), 516–540. https://doi.org/10.1108/APJML-03-2018-0118
- Yousafzai, S. Y., Foxall, G. R., & Pallister, J. G. (2007). Technology acceptance: a meta-analysis of the TAM: Part 1. *Journal of Modelling in Management*, *2*(3), 251–280. https://doi.org/10.1108/17465660710834453