Artificial Intelligence Applications And Innovations Vol. 1 No. 4 (2024)

Article history:
Received 2 June 2024
Revised 27 July 2024
Accepted 01 September 2024
Published online 01 October 2024

Convergence of AI and Content Marketing in the Digital Transformation of Businesses

Maryam. Modiri[1], Nassim. Majidi Ghahrudi [2*], Ataollah. Abtahi[3], Mohammadreza. Rasouli[4]

[1] Department of Communication, Journalism and Media, Faculty of Social Sciences, Communication and Media Studies, Islamic Azad University of Central Tehran, Tehran, Iran
[2] Department of Communication, Journalism and Media, Faculty of Social Sciences, Communication and Media Studies, Islamic Azad University, Central Tehran Branch, Tehran, Iran*
[3] Department of Media & Culture management, science and research branch, Islamic Azad University, Tehran, Iran
[4] Department of Cultural and Media Studies, Faculty of Social Sciences, Communication and Media Studies, Islamic Azad University, Central Tehran Branch, Tehran, Iran

*** Corresponding author email address**: nas.majidi_ghahrodi@iauctb.ac.ir

Article Info

Article type:
Review Article

How to cite this article:
Modiri, M., Majidi, N., Abtahi, A., & Rasouli, M. (2024). Convergence of AI and Content Marketing in the Digital Transformation of Businesses. *Artificial Intelligence Applications and Innovations, 1*(4), 76-86.
https://doi.org/10.61838/jaiai.1.4.6

ABSTRACT

This study was conducted with the purpose of "developing and validating a model of the convergence of artificial intelligence and content marketing in the digital transformation of businesses." The research design followed a sequential exploratory mixed-method approach. In the qualitative phase, semi structured interviews were conducted with experts in communication, digital marketing, and artificial intelligence. The data were analyzed using the thematic network approach at three levels—components, dimensions, and core concepts. The output of this phase yielded five principal concepts: "content creation," "use of automation tools," "efficiency of data analysis," "effective interaction and content distribution," and "enhancement of decision making," which formed the basis for developing the quantitative instrument. The content validity of the items was confirmed through expert judgment and the Content Validity Ratio (CVR) with a threshold of 0.62. In the quantitative phase, the final questionnaire was distributed online, and 489 valid responses were collected. A confirmatory factor analysis (CFA) was performed; nine items with low factor loadings, as well as the "search engine optimization" factor, were removed to improve model fit. The measurement model fit indices and chi square ratio were found to be satisfactory. The final outcome presents a coherent and reliable framework that clarifies the linkage between the technical capacities of artificial intelligence and the content strategic needs of startups, offering a practical roadmap for designing and assessing content quality, implementing automation, optimizing distribution, and strengthening data driven decision making.

Keywords: *Content Marketing, Startups, Artificial Intelligence Technologies*

1. Introduction

The rapid transformations in digital technologies have reshaped business structures and, by lowering entry barriers and creating new economic platforms, have presented fresh opportunities for growth and innovation for startups [1-3]. Startups, particularly following the surge in e-commerce during the COVID-19 pandemic, play a crucial role in economic development and job creation. Within this context, marketing is recognized as a key success factor for customer acquisition and retention, product introduction, and establishing a competitive advantage [4, 5]. Content marketing, which focuses on the production and distribution of relevant and valuable content, is considered an efficient approach for customer engagement and enhancing trust and loyalty. For resource-constrained startups, it represents a low-cost and effective option for communicating with the target market and achieving sustainable growth [5-8].

Despite these advantages, startups face financial and human resource constraints, a lack of content creation expertise, and poor brand awareness in implementing content marketing—issues that complicate customer acquisition, retention, and the formation of effective engagement [9-13]. In this context, Artificial Intelligence (AI), as an enabling technology, can analyze big data, identify preferences, and generate personalized content, thereby improving the efficiency of marketing activities and reducing costs [14]. However, realizing these capabilities often requires funding and capital support [15]. Successful examples of recommendation systems like Amazon and Netflix demonstrate that AI improves engagement and loyalty rates by increasing the accuracy of customer behavior analysis and optimizing strategies, which can serve as a positive model for startups [14].

For effective leveraging, a four-stage cycle is essential: accurate analysis of audience needs based on behavioral data, the production of customized and responsive content, targeted distribution across digital platforms, and continuous performance evaluation for strategic refinement. The integration of content, personalization [16], process automation [17] predictive analytics [18], and continuous measurement [19] within this framework can create a sustainable competitive advantage. The experience of advanced ecosystems like Silicon Valley suggests that AI should be regarded not merely as a complementary tool but as a fundamental component of the content marketing architecture. This is particularly prominent in B2B businesses due to the complexity of the purchase decision, the need for specialized content, and the importance of trust-based relationships. [20] However, a review of studies indicates that the prevalent focus of research, both domestically and internationally, has been on general aspects of digital marketing or content production, and less attention has been paid to integrated models of artificial intelligence with content marketing within the startup context [21].

In Iran, studies such as identifying mental models of marketing in FinTech startups [22] or examining smart marketing campaigns [23] have been conducted, but they have not offered a comprehensive framework for the systematic integration of AI and content marketing. Furthermore, they have primarily focused on technical optimization or human resource training without achieving a comprehensive operational model suitable for the resource constraints of startups. At the international level, although frameworks such as MARK-GEN have addressed the challenges of creative content generation, and emphasis has been placed on product-content-market fit in startups, and the role of AI-based [5] personalization in brand loyalty has been highlighted, a gap remains in providing localized and implementable solutions for startups. Simultaneously, the ethical dimensions and security risks raised in the literature [23] have rarely been incorporated into integrated marketing models. Given the practical necessity for Iranian startups to access cost-effective tools to overcome financial and human resource constraints, the need for research that concurrently integrates technical, human, and ethical dimensions is amplified.

In the dynamic landscape of the digital economy, content marketing has become a fundamental pillar of startup marketing strategies. Amidst this, Artificial Intelligence (AI) technologies—with capabilities such as big data analysis, advanced personalization, machine learning, and marketing automation—have provided novel opportunities to enhance the effectiveness and efficiency of this type of marketing. The targeted utilization of AI can improve content quality, increase the speed and accuracy of audience behavior analysis, and enable smarter design of content distribution channels. However, leveraging these technologies requires a precise understanding of the influencing components and a smart confrontation of challenges such as technical complexity, ethical considerations, security risks, and the issue of user trust; these issues are more prominent in nascent startup environments with limited resources.

Therefore, this research has been conducted with the aim of identifying and analyzing the key dimensions of utilizing AI in startup content marketing and seeks to answer the central question: What are the strategic components related to content quality, automation tools, data analysis efficiency, content distribution methods, and smart decision-making processes that enable startups to effectively leverage AI, improve user engagement, and strengthen their competitive position in the market? In this regard, the five main research questions are: 1) What are the dimensions and influencing components of content quality in startup content marketing using AI? 2) What are the dimensions and influencing components of utilizing automation tools in startup marketing using AI? 3) What are the dimensions and influencing components of data analysis efficiency in startups using AI? 4) What are the dimensions and influencing components of effective content distribution and user engagement in startups using AI? 5) What are the dimensions and influencing components of improving user and startup decision-making using AI?

2. Research Methodology

The present research methodology is of an exploratory mixed-methods type, designed and implemented in two qualitative and quantitative stages. In the first step, with the aim of identifying the dimensions and components of Iranian users' attitudes towards content marketing in AI-based startups, the twelve-step netnography approach by Kucuk [24] was employed alongside online semi-structured interviews with experts. The target population for the qualitative phase included specialists in communication sciences, media management, artificial intelligence, and startup marketing managers, who were purposefully selected based on criteria of specialized competence. Data were collected, recorded, and transcribed verbatim after obtaining informed consent. Subsequently, the data were analyzed using the thematic analysis method within the MAXQDA software, version 3, through three steps: "extraction of basic components," "categorization into organizing dimensions," and "synthesis into main concepts." To evaluate the content validity of the constructs derived from the analysis, the Content Validity Ratio (CVR) was calculated and documented based on the Lawshe method, relying on expert opinions. Thus, the initial structure of the conceptual model, comprising dimensions, components, and measurable indicators, was formulated to serve as the basis for the quantitative phase.

2.1. Quantitative Phase

The second stage, aimed at empirically testing the extracted conceptual model, employed a descriptive correlational research design. Based on this, a researcher-made questionnaire, derived from the qualitative phase findings, was designed. After confirming its validity and reliability (using Cronbach's Alpha), it was distributed online among individuals who make online purchases from Iranian startups and have participated in AI-based content marketing processes. A convenience sampling method was utilized, and based on Morgan's table, the minimum required sample size was estimated to be 385 participants; to enhance precision, 489 completed questionnaires were collected and entered into the analysis.

Quantitative data analysis was conducted relying on Confirmatory Factor Analysis (CFA) using R software, version 4.5.1, and the lavaan package. Within this framework, the measurement model for the questionnaire constructs was defined, reliability and validity indices were calculated, and necessary decisions regarding the retention or removal of items were made solely based on theoretical considerations and psychometric criteria. Throughout all stages, research ethics principles—including confidentiality, the right to withdraw, and the exclusive academic use of data—were strictly adhered to.

3. Research Findings

3.1. Qualitative Section

This section presents the qualitative findings derived from the analyzed data, collected with the objective of designing the model for "AI-Based Content Marketing for Startups." The analysis was conducted based on the "Thematic Network" framework, following the thematic analysis method, to organize the data across three levels: components, organizing dimensions, and core concepts. In response to one main question, broken down into five sub-issues, five cohesive core concepts were extracted: 1. Content Quality, 2. Utilization of AI-Based Marketing Automation Tools, 3. Data Analysis Efficiency in Optimizing Marketing Performance, 4. Effective Content Distribution and User Engagement, and 5. Improvement of Decision-Making Processes in Startup Environments. These concepts were shaped through expert interviews, and the codes were systematically reviewed at the aforementioned three levels to maintain focus on key implications, conceptual distinctiveness, and the measurability of each dimension.

the outcome of the interview analysis indicates that the concept of "Content Creation" forms the qualitative foundation of the model, comprising 9 dimensions and 33 components. These range from creating customer value and audience identification to personalization, search engine optimization, measurability, cognitive and emotional impact, informational value, capital attraction, and brand reinforcement. Following the execution chain, "Utilizing Automation Tools" is organized across 5 dimensions and 20 components, covering functionalities such as data analysis and monitoring, specialization, customer journey guidance, process automation, and system integration. This section directly links to improving the accuracy, speed, and systematic tracking of campaigns. "Data Analysis Efficiency," with 2 dimensions and 8 components, emphasizes the convergence of technical capabilities with ethical considerations, demonstrating that fairness, transparency, trustworthiness, and content relevance are prerequisites for analytical productivity and a superior user experience. In "Effective Content Interaction and Distribution," 22 components are grouped into 4 dimensions, encompassing deep audience understanding, selection of appropriate communication platforms, intelligent timing, real-time interaction measurement, and alignment with behavioral trends. Thus, the path for designing dynamic campaigns and increasing engagement is mapped out. Finally, "Improving Decision-Making," with 3 dimensions and 16 components, illustrates that data-driven decision-making, predictability, and explainability are the pillars of trust and efficiency in startup environments. This includes real-time analysis, prioritizing options, and personalized, explainable recommendations, collectively supporting the content marketing cycle from creation to execution and evaluation in an integrated and trackable manner.

3.2. *Reliability of Collected Data*

To ensure accuracy and credibility in the content analysis of the interviews, the reliability of the coding process was assessed using two methods: test-retest reliability and inter-coder agreement reliability. In the test-retest method, the researcher re-coded two selected interviews after a specific time interval to measure the consistency of their performance over time. In Interview No. 1, the total number of codes was 13, with 5 agreements, resulting in an agreement percentage of 76.9%. In Interview No. 2, the total number of codes was 10, with 4 agreements, equivalent to 80% agreement. Overall, out of 23 codes, 9 were identified identically in the two phases, and the test-retest reliability coefficient, calculated using the formula Agreements×2÷Total Codes×100\text (Agreements) \times 2 \div \text [Total Codes] \times 100Agreements×2÷Total Codes×100, was computed as 78.3%. This rate, which is higher than the acceptable threshold of 60%, indicates satisfactory stability and coherence in the coding over time.

To measure inter-coder agreement, an associate researcher familiar with the research topic was invited as the second evaluator to independently code two interviews. In Interview No. 1, the total number of codes was 14, with 6 agreements recorded, corresponding to an 85.7% agreement. Interview No. 2 yielded 19 total codes with 8 agreements, showing an agreement percentage of 84.2%. Thus, out of a total of 33 codes across these two interviews, 14 codes were similarly identified and applied by both coders, resulting in an inter-coder reliability coefficient calculated at 84.8%. This level of agreement, significantly above the 60% threshold, signifies excellent scientific coordination and precision between the two evaluators during the analysis process. Based on the results of both methods—78.3% for test-retest and 84.8% for inter-coder agreement—it can be concluded that the content analysis of the conducted interviews possesses a high degree of stability, coherence, and trustworthiness. These coefficients surpass the acceptable level of 60% and emphasize the scientific validity and dependability of the qualitative findings of this research.

3.3. *Content Validity of Extracted Dimensions*

To assess the content validity of the key dimensions and components in the domain of AI-driven content marketing for startups, the opinions of 10 experts were gathered, and the Lawshe's content validity ratio (CVR) was calculated. The acceptance threshold for 10 evaluators is 0.62, and all components surpassed this value. In "Content Quality and Tools," the components of measurability and cognitive and affective impact were reported with a CVR of 1.00. Furthermore, customer value creation, audience identification, content personalization, search engine optimization, informational value, capital attraction, and brand reinforcement all had a CVR of 0.80.

Within "Utilization of Automation Tools," the components of data analysis and monitoring, specialization, customer journey, and system integration had a CVR of 1.00, while process automation had a CVR of 0.80. In "Data Analysis Efficiency," concerns regarding algorithms and intelligence received a CVR of 1.00, and personalization and content appropriateness obtained a CVR of 0.80.

For "Effective Content Interaction and Distribution," the four components of audience understanding, communication platforms, user behavior analysis, and trend identification were all validated with a CVR of 1.00. In "Decision-Making," the three components of data-driven decision-making, predictability, and explainability all had a CVR of 1.00.

Therefore, given that all reported values are equal to or exceed the threshold of 0.62, it can be concluded that the level of expert agreement regarding the necessity of these components is high, and the content validity of the extracted dimensions for use in the research model is confirmed. Finally, the final research model, derived from the qualitative findings, is presented in Figure 1.

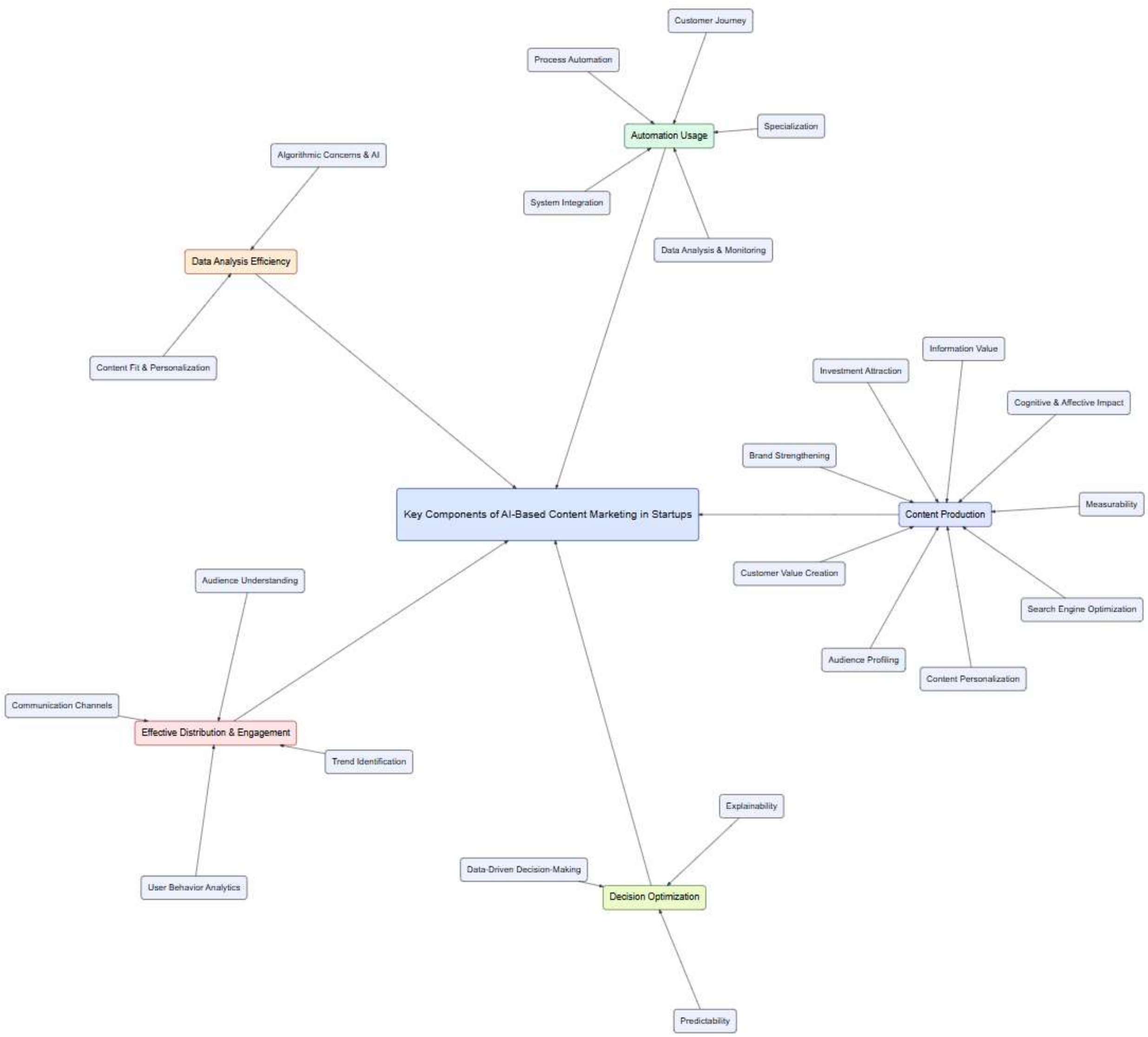

Figure 1. Conceptual Model of AI-Based Content Marketing in Startups (Derived from Qualitative Findings)

3.4. Quantitative Section

The process of questionnaire formulation was based on the findings of the qualitative section, encompassing the systematic extraction of items from the concepts, dimensions, and components derived from thematic analysis. In the initial step, a preliminary set of 56 items was formulated and submitted to 10 experts in digital marketing, consumer behavior, and research methodology for content validity assessment. The content validity of each item was measured using Lawshe's Content Validity Ratio (CVR) index, and considering the Lawshe table, the minimum acceptable value for 10 evaluators was set at 0.62. In this stage, 14 items were revised and corrected due to obtaining a value lower than the threshold, and subsequently, along with supplementary items proposed by the experts, a more comprehensive version was developed. Thus, the 88-item version, following final expert approval, served as the basis for quantitative data collection. The questionnaire was distributed online among customers and users of active startups in Iran, and 489 valid responses were collected for statistical analysis.

3.5. Construct Reliability and Measurement Model Fit

To assess construct validity, Confirmatory Factor Analysis (CFA) was executed in two steps. Prior to estimation, the multivariate normality assumption was examined using the Energy Test; the calculated MVES value was 4.96 with a significance level of 0.07, indicating the acceptance of normality and permitting the application of the Maximum Likelihood Estimation (MLE) method. In the first step, the initial structure comprising 88 items was evaluated through CFA, and due to low factor loadings of certain items and their negative impact on model fit, 9 items coded 2, 10, 11, 12, 34, 50, 54, 81, and 83 were removed. Furthermore, the "Search Engine Optimization" factor was excluded from the "Content Quality and Tools" dimension. Subsequently, the revised model with 78 items was estimated, and the fit indices were found to be in the desirable range: CFI was reported as 0.966, TLI and NNFI were both 0.965, IFI was 0.966, and RNI was 0.966, all of which are above 0.90, demonstrating an appropriate fit. The Chi-square to degrees of freedom ratio (χ2/df\chi^2/dfχ2/df) was calculated as 1.09, and the RMSEA index was obtained as 0.014 with a 90% confidence interval ranging from 0.010 to 0.017, which is less than 0.05, signifying a very low approximate model error. Additionally, the SRMR value was reported as 0.042. Moreover, the Goodness of Fit Index (GFI) fell within the range of 466 to 473, which is above the conventional minimum value of 200, supporting the adequacy of the sample size and the appropriate fit of the measurement model. Accordingly, the revised model demonstrated a satisfactory fit with the research data, and the final factor structure of the questionnaire was confirmed.

According to the findings, all measurement paths demonstrated standardized factor loadings exceeding the minimum criterion of 0.35, and the z statistics were significant ($p < 0.01$), indicating satisfactory validity and internal consistency among the constructs.

At the first order construct level, the observed items confirmed that each of the main dimensions of the model had the capability to explain its relevant variables. The second order constructs also exhibited significant loadings on their respective sub indicators. For instance, the factor "content quality and tools" showed loadings ranging from 0.64 to 0.66 on the dimensions of customer value creation, audience identification, content personalization, measurability, cognitive and emotional impact, informational value, capital attraction, and brand enhancement, playing a pivotal role in explaining the model.

The factor "use of automation tools" displayed loadings between 0.53 and 0.69 on data analytics and monitoring, customer experience specialization, customer journey automation, marketing process automation, and system integration, revealing that this dimension effectively covers digital marketing behaviors.

Similarly, the factor "data analysis efficiency" showed loadings of 0.52 and 0.53 on algorithm related concerns and content personalization, whereas the factor "effective content interaction and distribution" exhibited loadings between 0.59 and 0.74 on audience understanding, communication platforms, user behavior analysis, and trend identification, underscoring its key role in enhancing content interaction and dissemination.

The factor "decision making" showed loadings between 0.59 and 0.74 on data driven decision support, predictability, and explainability, indicating that this dimension strengthens the model's capability to encompass strategic, data based decisions.

Overall, the results presented provide strong evidence of construct validity and satisfactory measurement model fit, confirming the robustness of the factorial structure of the AI based content marketing questionnaire for startups. The tested confirmatory factor analysis (CFA) model is illustrated in Figure 2.

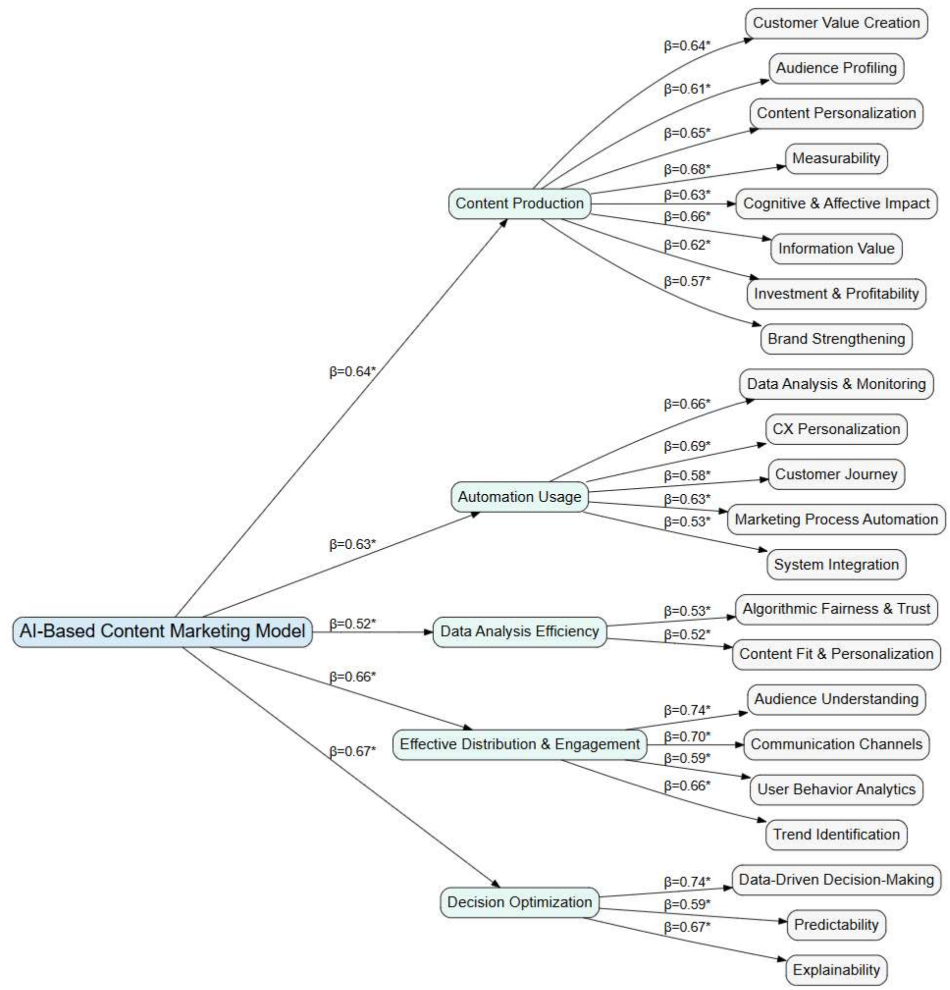

Figure 2. Conceptual Model of AI-Based Content Marketing in Startups (Derived from Quantitative Findings)

4. Conclusion

This research was conducted with the aim of systematically explaining the key dimensions and components of content marketing in startups utilizing artificial intelligence technology. It proceeded in two stages within an exploratory sequential mixed-methods design. In the qualitative phase, five research questions pertaining to content production, utilization of automation tools, data analysis efficiency, effective content distribution, user interaction, and decision-making improvement were formulated. Expert interviews were analyzed to organize evidence at three levels: "component, dimension, and main concept," and an initial conceptual framework was extracted. Subsequently, in the quantitative phase, based on this framework, a measurement instrument was developed, and its content validity was assessed. By collecting survey data, the measurement model was examined using structural equation modeling/confirmatory factor analysis. The outcome of both phases has provided a practical and reliable roadmap for implementing artificial intelligence in startup content marketing strategies. This roadmap extends from content creation and personalization layers to customer journey automation, predictive analytics, and explainable decision-making, ultimately leading to the enhancement of strategy efficiency, effectiveness, and agility.

The findings of this research, in response to the first question, indicate the multifaceted and complex dimensions of content quality in AI-driven content marketing for startups. These dimensions include creating customer value, precise audience identification, content personalization, search engine optimization, measurability of effectiveness, cognitive and affective impact, informational value, capital attraction, and brand reinforcement. These results are aligned with previous studies; for instance, [25] demonstrated that content optimization based on search engine algorithms and analysis of content performance through AI tools plays a key role in enhancing visibility and effectiveness of marketing campaigns. Furthermore, attention to the cognitive and emotional effects of content, consistent with the findings of [26], is crucial for fostering deeper engagement and building audience trust. This is particularly relevant in dynamic environments like startups, where competition for customer attention and loyalty is intense. Finally, the capabilities of AI in facilitating capital attraction and brand reinforcement, especially through creative content generation and targeted storytelling, align with the results of. This study [27] indicates that intelligent content marketing can significantly contribute to shaping brand perception and establishing a sustainable competitive advantage, in addition to increasing sales.

The findings from the analysis of the second question revealed five key dimensions of AI-based marketing automation, each playing a pivotal role in improving performance and optimizing marketing processes in startups. These dimensions are: precise data analysis and monitoring, customer experience personalization, complete customer journey management, marketing process automation, and integration of various marketing systems. These results are consistent with previous studies, such as [28], which emphasize the vital role of automation in enhancing targeting accuracy and improving campaign efficiency. Additionally, as noted by [29], the ability to create continuous data streams and real-time analysis of results enables immediate strategy adjustments and continuous improvement of marketing processes, thereby maintaining a competitive edge in dynamic and competitive startup environments. Overall, the findings suggest that AI-based marketing automation not only enhances operational efficiency but also leads to more effective engagement and higher customer satisfaction by providing deeper insights and more intelligent responses to customer needs.

The results concerning the third question indicate that the "Data Analysis Efficiency" rests upon the confluence of two components: first, considerations related to the algorithm itself and the artificial intelligence processes, including reliability, transparency, and error control; second, "Content Personalization and Appropriateness" relative to the audience's context and needs. The coherent linkage between these two establishes the optimality of the data chain as a prerequisite for efficiency. This spans from the quality and integrity of the input data and the selection or calibration of the model to the scalability of estimations and the ability to explain the results to stakeholders. This interpretation aligns with current literature: [14] specifies that analysis efficiency leads to a significant improvement in effectiveness only when data-driven personalization is supported by a sound data infrastructure and continuous feedback loops. Furthermore, [14] emphasizes that the true impact of AI on marketing decision-making hinges on linking the technical capability of analysis with the requirements of trust, transparency, and explainability for stakeholders. Based on this, whenever "Content Appropriateness" is enhanced, the model's data cycle functions more efficiently, and conversely, any disruption in algorithmic quality or explainability can constrain analysis efficiency and, consequently, personalization accuracy.

In response to the fourth question, the vital role of AI in enhancing user engagement and effective content distribution was highlighted: deep audience understanding achieved through sentiment and behavior analysis, intelligent selection of communication platforms tailored to audience characteristics, real-time analysis of user behavior, and optimal content publishing timing. According to [30], these components are facilitated by tools such as sentiment analysis, market trend monitoring, and intelligent content distribution algorithms. Moreover, [25] demonstrates that extensive and real-time data analysis enables precise content personalization and the selection of the best publishing time and channel, leading to increased effective engagement. Additionally, the utilization of participatory mechanisms, such as online competitions and surveys—supported by AI automation and intelligence—drives deeper engagement and greater loyalty. This is a point also confirmed by [31] in strengthening brand positioning and establishing a sustainable competitive advantage for startups.

In response to the fifth question, three dimensions—"data-driven decision-making," "predictability," and "explainability"—were identified as central to enhancing the quality of strategic and operational decisions. Data-driven decision-making relies on processing vast amounts of customer, market, and sales data, extracting precise and timely insights through advanced analytical tools such as Tableau and Power BI. Predictability, using machine learning algorithms and forecasting platforms like TensorFlow and scikit-learn, illuminates future market trends and customer behavior. According to evidence from [20, 32, 33], this leads to improved marketing strategies and increased return on investment. Explainability, as a condition for trusting intelligent systems, clarifies the logic of recommendations using tools like LIME and Fairlearn, enabling ethical assessment and accountability—an approach that, according to [34], is essential for the acceptance and defensibility of decisions. In conclusion, the judicious application of AI enhances the flexibility and competitiveness of startups in complex environments, providing the capacity for efficient responses to environmental challenges.

The results of this mixed-methods exploratory research indicate that artificial intelligence plays a key and multifaceted role in transforming content marketing for startups. In the qualitative phase, a cohesive framework was extracted, covering five interconnected areas: "content creation," "utilization of automation tools," "data analysis efficiency," "effective content engagement and distribution," and "decision-making improvement." In the quantitative phase, this structure was validated through confirmatory factor analysis and refinement of items, thereby providing an integrated and measurable roadmap for AI implementation across the entire content marketing cycle. The convergence of findings from both phases suggests that startups can achieve improved efficiency, reduced costs, and increased effectiveness by simultaneously focusing on content quality and measurability, deploying automation aligned with the customer journey, real-time monitoring and analysis of interactions, and adopting data-driven and explainable decisions. Alongside technical advantages, attention to ethical dimensions, transparency, and algorithmic accountability is a prerequisite for gaining the trust of managers and users, and for fostering a foundation for sustainable growth. Based on the qualitative-quantitative synthesis, targeted investment in data analysis infrastructure, intelligent automation, and predictive tools is recommended. Concurrently, policies for transparency and explainability for AI outputs must be developed and implemented to enhance organizational acceptance and customer satisfaction. Adapting marketing models to the characteristics of different market segments and optimizing the allocation of limited startup resources can enhance campaign returns.

Limitations include the qualitative phase's reliance on the perspectives of startup domain experts and industry-dependent generalizability. For future research, testing the model in different industries and timeframes, integrating it with complementary technologies such as advanced machine learning, blockchain, and the Internet of Things, and evaluating the impact of explainability mechanisms on user behavior and campaign performance are recommended. Overall, this research, by integrating qualitative intuition and quantitative evidence, provides a practical and scientific basis for designing, implementing, and evaluating AI-based content marketing in startups, illuminating the path toward more precise, agile, and trustworthy marketing.

Authors' Contributions

All authors equally contributed to this study.

Declaration

None.

Transparency Statement

None.

Acknowledgments

None.

Declaration of Interest

The authors declare that they have no conflict of interest. The authors also declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

Not applicable.

References

[1] M. M. Azeem and B. Kotey, "Innovation in SMEs: The role of flexible work arrangements and market competition," *The International Journal of Human Resource Management,* vol. 34, no. 1, pp. 92-127, 2023, doi: 10.1080/09585192.2021.1961162.

[2] R. Guo, H. Yin, and X. Liu, "Coopetition, organizational agility, and innovation performance in digital new ventures," *Industrial Marketing Management,* vol. 111, pp. 143-157, 2023, doi: 10.1016/j.indmarman.2023.04.003.

[3] D. Rohn, P. M. Bican, A. Brem, S. Kraus, and T. Clauss, "Digital platform-based business models-An exploration of critical success factors," *Journal of Engineering and Technology Management,* vol. 60, p. 101625, 2021, doi: 10.1016/j.jengtecman.2021.101625.

[4] C. Oztabak, "Reframing startup marketing strategy with product-content-market fit," *Giresun Üniversitesi İktisadi ve İdari Bilimler Dergisi,* 2024. [Online]. Available: https://dergipark.org.tr/en/pub/guiibd/issue/89344/1491114.

[5] S. Razmanova and O. V. Andrukhova, "Oilfield service companies as part of economy digitalization: Assessment of the prospects for innovative development," *Journal of Mining Institute,* vol. 244, pp. 482-492, 2020, doi: 10.31897/pmi.2020.4.11.

[6] M. Agarwal and A. Sharma, "Digital marketing of startup businesses," *Journal of Scientific Research and Technology,* pp. 8-29, 2024, doi: 10.61808/jsrt94.

[7] M. A. Halim and E. Ermiani, "Startups in the digital era: Exploring the role of digital marketing strategy through a literature review," *Strata International Journal of Social Issues,* vol. 1, no. 2, pp. 161-170, 2024. [Online]. Available: https://journals.stratapersada.com/index.php/sijosi/article/view/260.

[8] S. A. Mogull, "Strategy of technical content marketing in an entrepreneurial tech company: Using the funnel-bucket model to guide the message and media," *Technical Communication,* vol. 70, no. 2, pp. 43-54, 2023, doi: 10.55177/tc862277.

[9] O. Ashurbaev and G. Rustamova, "Challenges faced by startups and the ways to overcome them," *Multidisciplinary Journal of Science and Technology,* vol. 4, no. 12, pp. 891-897, 2024. [Online]. Available: http://mjstjournal.com/index.php/mjst/article/view/2290.

[10] T. Hassija, S. Watts, and M. Goel, "Fintech startups challenges and suggested strategies to overcome," in *Revolutionary Challenges and Opportunities of Fintech*: Apple Academic Press, 2024, pp. 71-89.

[11] J. Kask and G. Linton, "Navigating the innovation process: Challenges faced by deep-tech startups," in *Contemporary Issues in Industry 5.0: Towards an AI Integrated Society*: Cham: Springer Nature Switzerland, 2025, pp. 197-219.

[12] A. Kislukhin, *How to run marketing in startups efficiently?* 2024.

[13] F. Vahidzadegan and A. Zangiabadi, "Examining the role of brand image in the brand equity of Isfahan tourism from the perspective of domestic tourists," *Tourism & Development,* vol. 10, no. 4, pp. 63-72, 2021. [Online]. Available: https://www.itsairanj.ir/article_131543.html?lang=en.

[14] V. Kumar, A. R. Ashraf, and W. Nadeem, "AI-powered marketing: What, where, and how?," *International Journal of Information Management,* vol. 77, p. 102783, 2024, doi: 10.1016/j.ijinfomgt.2024.102783.

[15] S. Kuchi and S. Gupta, "Value-creation strategies for e-commerce businesses," *IIM Kozhikode Society & Management Review,* vol. 12, no. 2, pp. 234-249, 2023, doi: 10.1177/22779752231153482.

[16] A. Hassan, F. A. Mohammed, and A. Y. Seyadi, "Artificial intelligence applications for marketing," in *Studies in Systems, Decision and Control*, vol. 528, 2024, pp. 607-618.

[17] A. B. Sarin and S. Sharma, "Harmonizing AI and human interaction: Enhancing modern marketing strategies," in *Balancing Automation and Human Interaction in Modern Marketing*, 2024, pp. 151-174.

[18] M. Alghizzawi, E. Ahmed, I. Ezmigna, A. A. R. Ezmigna, and F. Omeish, "The relationship between artificial intelligence and digital marketing in business companies," in *Studies in Systems, Decision and Control*, vol. 525, 2024, pp. 885-895.

[19] A. M. A. Alqudah and et al., "Artificial intelligence in design and impact on electronic marketing in companies," *Journal of Ecohumanism,* vol. 3, no. 4, pp. 170-179, 2024, doi: 10.62754/joe.v3i4.3480.

[20] C. S. Lee, P. Y. S. Cheang, and M. Moslehpour, "Predictive analytics in business analytics: Decision tree," *Advances in Decision Sciences,* vol. 26, no. 1, pp. 1-29, 2022, doi: 10.47654/v26y2022i1p1-29.

[21] S. Vasundhara, K. S. Venkatesh, V. Manimegalai, P. Sundharesalingam, S. Sathyakala, and S. Boopathi, "AI-powered marketing revolutionizing customer engagement through innovative strategies," in *Cases on AI Ethics in Business*, 2024, pp. 21-46.

[22] M. Behzadnia, S. Nayebzadeh, S. H. Hatami-Nasab, and M. R. Dehghan Ashkezari, "Scientific/mental typology of marketing performance in fintech startups using the Q-methodology," *Journal of New Marketing Research,* vol. 14, no. 3, pp. 97-134, 2023. [Online]. Available: https://nmrj.ui.ac.ir/article_29131_en.html?lang=en.

[23] Y. Elkhatibi and R. Benabdelouhed, "Digital revolution: How AI is transforming content marketing," *International Journal of Advanced Multidisciplinary Research and Studies,* 2024. [Online]. Available: https://www.multiresearchjournal.com/admin/uploads/archives/archive-1728911168.pdf.

[24] R. Kozinets, *Netnography: Redefining a Method for Studying Relationships and Culture in Networked Environments (M. Rasouli and P. Nematollahi, Trans.)*. Tehran: Office for Media Studies and Planning, 2021.

[25] Y. K. Dwivedi *et al.*, "Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy," *International Journal of Information Management,* vol. 57, p. 102994, 2021, doi: 10.1016/j.ijinfomgt.2019.08.002.

[26] K. N. Lemon and P. C. Verhoef, "Understanding customer experience throughout the customer journey," *Journal of Marketing,* vol. 80, no. 6, pp. 69-96, 2016, doi: 10.1509/jm.15.0420.

[27] E. Bonetti, A. Mattiacci, and M. Simoni, "Communication patterns to address the consumption of PDO products," *British Food Journal,* vol. 122, no. 2, pp. 390-403, 2020, doi: 10.1108/BFJ-03-2019-0204.

[28] D. Chaffey and F. Ellis-Chadwick, *Digital Marketing*. Pearson UK, 2019.

[29] M. Wedel and P. K. Kannan, "Marketing analytics for data-rich environments," *Journal of Marketing,* vol. 80, no. 6, pp. 97-121, 2016, doi: 10.1509/jm.15.0413.

[30] T. Davenport, A. Guha, D. Grewal, and T. Bressgott, "How artificial intelligence will change the future of marketing," *Journal of the Academy of Marketing Science,* vol. 48, no. 1, pp. 24-42, 2020, doi: 10.1007/s11747-019-00696-0.

[31] G. Muchenje and M. Seppänen, "Unpacking Task-Technology Fit to Explore the Business Value of Big Data Analytics," *International Journal of Information Management,* vol. 69, p. 102619, 2023, doi: 10.1016/j.ijinfomgt.2022.102619.

[32] P. B. Pires, J. D. Santos, and I. V. Pereira, *Digital Marketing: Analyzing Its Transversal Impact*.

[33] A. Unalp, *AI-Powered Business Insights: Leveraging Data Mining for Strategic Market Analysis*. 2024.

[34] C. Rudin, C. Chen, Z. Zhang, H. Huang, L. Semenova, and C. Zhong, "Interpretable machine learning: Fundamental principles and 10 grand challenges," *Statistical Surveys,* vol. 16, pp. 1-85, 2022, doi: 10.1214/21-SS133.