Mednarodno inovativno poslovanje
Journal of Innovative Business and Management

AI-based content analysis in marketing: methods, processes, and evidence from an empirical study

Christopher Zerres[1], Jürgen Seitz[2]

Abstract: The exponential growth of digital content has fundamentally transformed how organizations can observe, understand, and predict human attitudes and behaviors. In marketing and related domains, artificial intelligence (AI)-based content analysis has emerged as a critical analytical capability for extracting insights from unstructured data such as text, images, audio, and video. While prior research has extensively discussed individual methods, less is known about how organizations actually implement these approaches and integrate them into decision-making processes. Addressing this gap, this study pursues two objectives. First, it provides a structured overview of AI-based content analysis methods and proposes an end-to-end process model that emphasizes organizational integration rather than algorithmic performance alone. Second, it reports findings from an empirical survey of marketing managers and experts that examines the adoption, maturity, objectives, perceived benefits, and barriers associated with AI-based content analysis in practice.

Keywords: AI-based Content Analysis; Text Analysis; Image Analysis; Video Analysis; Multimodal Analysis

JEL classification: L21, M15, M31

Analiza vsebin, ki temeljijo na umetni inteligenci v marketingu: metode, procesi in dokazi iz empirične študije

Povzetek: Eksponentna rast digitalnih vsebin je temeljno spremenila način, kako lahko organizacije opazujejo, razumejo in napovedujejo človeška stališča ter vedenje. Na področju marketinga in sorodnih disciplin se je analiza vsebin, podprta z umetno inteligenco (UI), uveljavila kot ključna analitična sposobnost za pridobivanje vpogledov iz nestrukturiranih podatkov, kot so besedila, slike, zvok in videoposnetki. Čeprav so pretekle raziskave obsežno obravnavale posamezne metode, je manj znanega o tem, kako organizacije te pristope dejansko uvajajo in vključujejo v procese odločanja.
Da bi zapolnila to vrzel, raziskava sledi dvema ciljema. Prvič, ponuja strukturiran pregled metod analize vsebin, podprtih z umetno inteligenco, ter predlaga celovit procesni model, ki poudarja organizacijsko integracijo in ne zgolj algoritmične zmogljivosti. Drugič, predstavlja ugotovitve empirične raziskave med vodji marketinga in strokovnjaki, ki preučuje stopnjo uporabe, zrelost, cilje, zaznane koristi in ovire, povezane z uporabo analize vsebin, podprte z umetno inteligenco, v praksi.

Ključne besede: analiza vsebin na osnovi umetne inteligence; analiza besedil; analiza slik; analiza videa; multimodalna analiza

Klasifikacija JEL: L21, M15, M31

[1]*Faculty of Media, Offenburg University, Offenburg, Germany, christopher.zerres@hs-offenburg.de*

[2]Faculty of Media, Offenburg University, Offenburg, Germany, juergen.seitz@hs-offenburg.de

DOI 10.32015/JIBM.2026.18.1.1

Mednarodno inovativno poslovanje = Journal of Innovative Business and Management

ISSN 1855-6175

INTRODUCTION

Individuals and organizations continuously generate vast amounts of textual, visual, and audiovisual content through social media, online communities, review platforms, websites, and internal information systems (e.g. customer relationship management systems). These internal and external data sources provide marketing-relevant insights into consumer attitudes, preferences, and needs, competitive activities, and broader market developments (Bär and Zerres, 2024; Peng et al., 2023).

Content analysis refers to the systematic selection, collection, preparation, analysis, interpretation, and presentation of digital content formats, including text, images, video, and audio. Advances in artificial intelligence (AI), particularly in machine learning, natural language processing, and computer vision, have significantly expanded the scope and scalability of content analysis. AI-based content analysis enables the automated detection of semantic meaning in text, the recognition of objects and emotions in images and videos, and the integration of information across multiple modalities (Peng et al., 2023).

Despite these technological advances, prior research indicates that a large proportion of unstructured data remains underutilized in organizations (Mahadevkar et al., 2024; Grewal et al., 2021; Schraml, 2025; Zhou et al., 2021). This shortfall is often attributed to missing process structures, limited analytical capabilities, and unresolved concerns related to transparency, ethics, and data protection (Zerres, 2025; Volkmar et al., 2021; De Bruyn et al., 2020; Vlačić et al., 2021). Against this background, the present study addresses the following objectives: (1) to synthesize and systematize AI-based content analysis methods relevant to marketing and related behavioral research contexts; (2) to propose a coherent process model that highlights the organizational prerequisites for effective use; and (3) to empirically examine how organizations currently adopt, implement, and evaluate AI-based content analysis.

1 PROCESS MODEL FOR AI-BASED CONTENT ANALYSIS

Difficulties in analyzing and exploiting unstructured data are often rooted in the absence of a clearly articulated and standardized analysis process. As a prerequisite, organizations must establish appropriate organizational conditions, including the allocation of financial, technical, and human resources, as well as the availability of relevant analytical and domain-specific expertise.

The proposed AI-based content analysis process follows a structured sequence of activities (see Figure 1). First, the analytical objective must be defined to ensure alignment with managerial decision needs. Second, relevant data are identified, collected, and extracted from internal and external sources. Third, the data are prepared through cleaning, transformation, and annotation. Fourth, AI-based analytical methods are applied to generate insights. Finally, the results are interpreted, communicated, and translated into concrete managerial actions. This end-to-end perspective underscores that analytical value does not arise from model performance alone but from the systematic integration of insights into organizational decision-making processes.

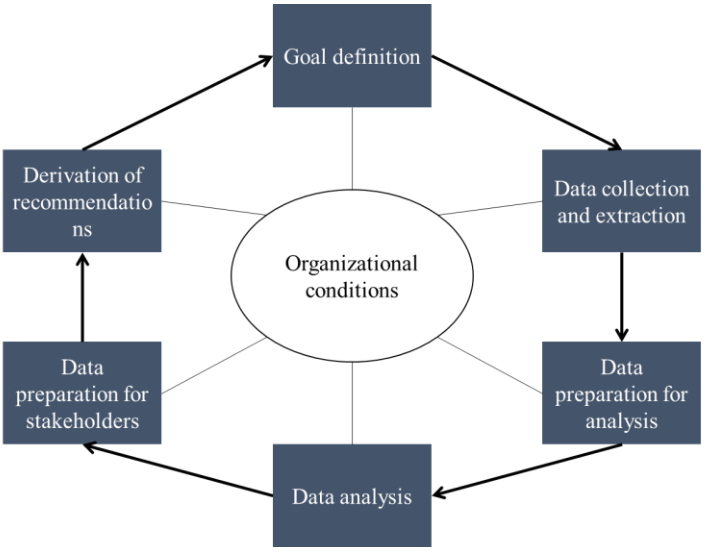

Figure 1. Process model for AI-based content analysis (Source: own development).

The conceptual contribution of the proposed model lies in its focus on the organizational integration of AI-based content analysis rather than on the development of individual analytical techniques. Existing research has primarily concentrated on methodological advances in the automated analysis of unstructured data, including text, images, audio, and video (Grewal et al., 2021; Peng et al., 2023; Barari & Eisend, 2024). These studies provide important insights into available analytical approaches and their potential applications but typically focus on specific data formats or analytical methods. Similarly, research on AI in marketing highlights both the opportunities and the challenges associated with AI adoption, including issues related to organizational capabilities, governance, and transparency (De Bruyn et al., 2020; Vlačić et al., 2021). Building on this literature, the present model conceptualizes AI-based content analysis as an end-to-end managerial workflow that links the definition of analytical objectives, the identification and preparation of relevant data sources, the application of AI-based analytical methods, and the interpretation and translation of analytical results into managerial actions. By structuring these activities into a coherent process and explicitly highlighting organizational prerequisites such as governance structures, analytical capabilities, and resource allocation, the model complements the predominantly method-oriented literature and provides a practice-oriented framework for integrating AI-based content analysis into marketing decision processes.

Beyond its methodological orientation, the proposed process model can also be interpreted through the lens of digital transformation and organizational capability development (Roy et al., 2025; Kumar et al., 2024; Vial, 2019). Prior research emphasizes that the value of AI in marketing does not arise solely from the availability of analytical techniques but from the ability of organizations to integrate these technologies into decision-making processes and value creation activities (Roy et al., 2025; De Bruyn et al., 2020; Vlačić et al., 2021). In this context, AI-based content analysis can be understood as an emerging analytical capability that enables firms to systematically extract insights from unstructured digital content such as text, images, and video (Grewal et al., 2021; Peng et al., 2023). While existing studies largely focus on methodological advances in computational content analysis (Berger et al., 2019; Barari & Eisend, 2024), less attention has been devoted to how these analytical techniques are embedded into organizational processes. The process model proposed in this study therefore conceptualizes AI-based content analysis as an end-to-end organizational capability that links analytical objectives, data sourcing and preparation, AI-based analysis, and the interpretation and operationalization of insights in managerial decision-making. By incorporating organizational prerequisites such as governance structures, analytical capabilities, and resource allocation, the model contributes to a better understanding of how AI-driven analytics can support the broader digital transformation of marketing functions.

Finally, the rapid development of generative AI technologies, particularly large language models and multimodal foundation models, further increases the importance of robust governance structures in AI-based content analysis. Generative AI systems are increasingly used not only for analyzing content but also for generating text, images, and other media, thereby expanding the scope of potential applications in marketing and communication. At the same time, these technologies raise new challenges related to transparency, bias, intellectual property, data protection, and accountability. Prior research has emphasized that the effective deployment of artificial intelligence in marketing requires appropriate governance mechanisms to ensure responsible and trustworthy use (De Bruyn et al., 2020; Vlačić et al., 2021). In the context of AI-based content analysis, this includes clear organizational responsibilities, monitoring and validation of model outputs, compliance with regulatory requirements such as data protection and copyright law, and the establishment of ethical guidelines for the use of automated analytical systems. Integrating such governance considerations into the analytical process is therefore a critical prerequisite for realizing the potential of AI-driven insights while mitigating associated risks.

2 AI-BASED CONTENT ANALYSIS METHODS IN MARKETING

Barari and Eisend (2024) propose an approach for systematizing possible methods, regardless of format type, which differentiates between supervised machine learning methods, unsupervised machine learning methods, and conventional techniques. The authors supplement each method with a number of key algorithms and techniques (see Figure 2).

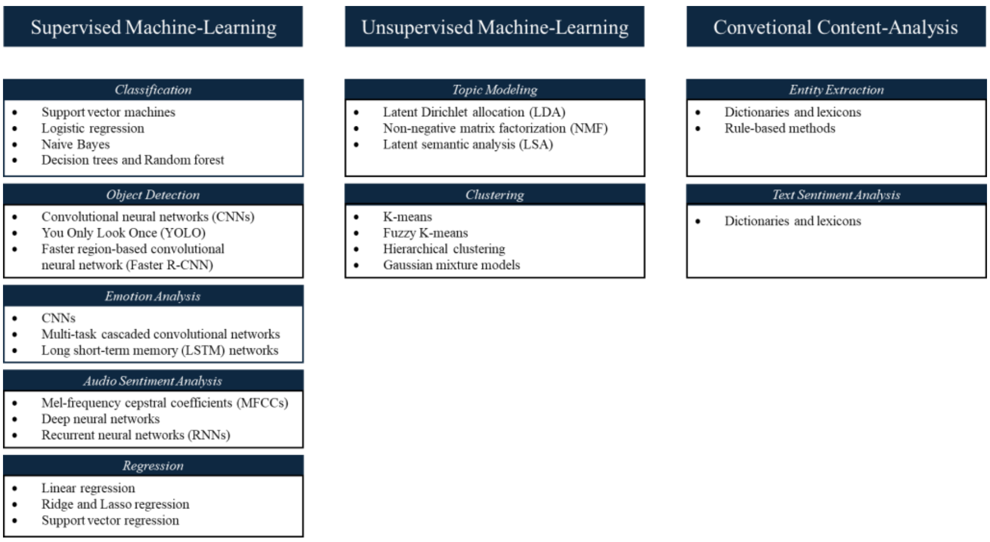

Figure 2. Systematization of AI-based content analysis methods (Source: own development based on Barari and Eisend, 2024).

2.1 Text Analysis

Despite the growing importance of images and videos, text content remains a central and important source of information for marketing. The findings can be used for both strategic and operational marketing decisions. Netzer et al. (2012), for example, were able to show that semantic analysis of online forums and blogs provides significant insights into market segments, competitive dynamics, and consumer needs. In their study, Liu et al. (2019)

demonstrate that linguistic features in social media posts, such as tonality and emotionality, are strong predictors of brand loyalty and recommendation. AI-based text analyses can also support the development of data-driven, target group-specific strategies. For example, sentiment analyses can be used to identify micro-segments (Barari and Eisend, 2024), which not only opens up new opportunities for brand positioning, but also allows for the personalization of marketing measures (Moon and Kamakura, 2017).

Three core text analysis approaches can be distinguished (Berger et al., 2019):

Entity extraction, which focuses on identifying relevant words or phrases (e.g., brands, attributes, emotions). Typical applications include brand buzz monitoring, sentiment analysis, trend detection, and the extraction of psychological states.

Topic extraction or topic modeling, which identifies latent themes across large text corpora. This approach is commonly used to summarize discussions, detect emerging consumer and market trends, and uncover unmet customer needs.

Relation extraction, which analyzes relationships between entities or concepts. Applications include identifying product-related problems, linking product attributes to positive or negative evaluations, and detecting events and their consequences, such as reputational crises.

2.2 Image Analysis

In addition to text, image content format is also important. Studies have shown that different image characteristics of posts on social media platforms influence engagement, for example (Li and Zhang, 2024; Philp et al., 2022). Such characteristics include color design, image composition, aesthetics, and emotions.

Computer vision models are an effective and efficient way to analyze images (Li and Zhang, 2024). Computer vision combines machine learning and image processing to offer sophisticated image recognition and classification functions, allowing visual content to be interpreted and analyzed independently (Li and Zhang, 2024; Mahadevkar et al., 2022). In their study, Li and Zhang (2024) systematize types of image analysis and investigate which computer vision models are suitable for the identified image analysis types. They differentiate between analyses related to visual conception (image classification, object recognition, and content understanding), emotional reception (facial expression detection, sentiment analysis, and themed sentiment analysis), and aesthetic evaluation (image quality, image aesthetics, style, and design) (Li and Zhang, 2024).

2.3 Video Analysis

In recent years, videos have become a very frequently used content format, especially on social media platforms (Schraml, 2025). Schraml (2025, p. 4) defines video analytics in marketing as "...automated or semi-automated techniques to extract, structure, and interpret information from video data, converting unstructured into structured data for quantitative analysis that produces generalizable insights." The analysis of videos allows companies, for example, to gain a better understanding of the efficiency of salespeople (Chakraborty et al., 2024), to better understand and improve the impact of communication campaigns (Yang et al., 2025), or to understand how users consume videos and how they then affect them (Xu et al., 2021).

Various areas can be considered when analyzing videos. These aspects are areas that have an impact on the effect of the video. Three possible categories could be video characteristics (e.g., video length and average scene length), video content (e.g., emotion recognition), and video aesthetics (e.g., resolution and contrast) (Zhou et al., 2021; Li et al., 2019). A comprehensive overview of current possibilities can be found in the literature review by Schraml (2025).

2.4 Multimodal Analysis

Multimodal content analysis refers to the algorithmic processing, linking, and interpretation of information from different modalities, such as text, image, speech, or audio (Baltrušaitis et al., 2019). Multimodal analysis enables machines to recognize complex relationships between language, image, and sound and to interpret content accordingly. The question is therefore how information from different modalities can be linked together in a meaningful way, both formally and algorithmically. In the context of multimodal machine learning, Baltrušaitis et al. (2019) present some key applications:

Audio-visual speech recognition (Mroueh et al., 2015)
Multimedia content indexing and retrieval (Lin et al., 2024)
Multimodal interaction and emotion recognition (Li et al., 2024)
Image captioning (Harzig et al., 2018)
Multimodal sentiment analysis (Xiao et al., 2022)

2.5 Tools

Numerous tools have now become established in science and practice for the content formats presented. Table 1 summarizes some commonly used tools. The selection of tools is based on Mahadevkar et al. (2024) (text), Li and Zhang (2024) (image and multimodal) and Schraml (2025) (video). The tools mentioned differ in terms of accessibility, data sovereignty, and adaptability. While cloud-based solutions (e.g., Google, AWS, Azure) offer rapid integration, open-source frameworks (e.g., Hugging Face, OpenCV, PyTorch) enable greater transparency and control over models and training data.

Table 1. Overview common tool and areas of application.
(source: own development)

Content format	Typical areas of application	Common tools/platforms
Text	(Automatic) text and sentiment analysis, topic and entity extraction, trend and segment analysis	OpenAI (GPT-5), Google Cloud Natural Language API, AWS Comprehend, Microsoft Azure Text Analytics, spaCy, Hugging Face, MonkeyLearn
Image	Object recognition, brand and emotion recognition, aesthetic analysis	Google Cloud Vision API, AWS Rekognition, Microsoft Azure Computer Vision, Clarifai, Imagga, OpenCV, PyTorch
Video	Scene, object, and emotion recognition, campaign and engagement analysis	Google Video Intelligence API, AWS Rekognition Video, Microsoft Azure Video Indexer, Viso Suite, Deepgram, Affectiva
Multimodal	Combination of text, image, audio, and video data; sentiment and context fusion	OpenAI CLIP, GPT-5 Vision, Google Gemini, DeepMind Flamingo, Hugging Face BLIP-2, LLaVA, ImageBind, IBM Watson Discovery, Runway

3 EMPIRICAL STUDY

3.1 Research Design and Sample

Building on the proposed process model and the described methods, an online survey was conducted among marketing managers and subject-matter experts to capture current organizational practices and perceptions related to AI-based content analysis. The survey was designed as an exploratory, cross-sectional study aimed at generating descriptive insights into the adoption, maturity, and perceived value of AI-based content analysis in marketing practice. The aim of the survey is to obtain a supplementary practical picture with regard to the following questions:

What is the current level of adoption of AI-based content analysis in organizations?
For which use cases is AI-based content analysis applied?
What benefits do organizations perceive from its use?
What challenges and barriers do organizations encounter?
To what extent is AI-based content analysis integrated into decision-making processes?

In the questionnaire established constructs and wording were adapted to the context of AI-based content analysis. Additional items were newly developed to reflect emerging practices not yet covered in existing scales. The questionnaire comprised five main sections: (1) respondent and firm characteristics, (2) existence and maturity of AI-based content analysis processes and governance structures, (3) methods and content formats employed (text, image, video, and multimodal), (4) perceived benefits and realized outcomes, and (5) organizational, technical, and regulatory barriers. Most items were measured using five-point rating scales, complemented by selected multiple-choice and open-ended questions to allow respondents to elaborate on their experiences.

The survey was conducted in July 2025 using an existing distribution list of marketing managers and experts from various industries in Germany, Austria and Switzerland. Participation was voluntary and anonymous. A total of 142 questionnaires were returned, of which 128 were fully completed and deemed usable for analysis. 14 responses were excluded due to substantial item nonresponse.

The resulting sample represents a heterogeneous set of firms with respect to industry focus, firm size, and market orientation. A majority of respondents were employed in service-oriented firms, and business-to-business (B2B) contexts were more prevalent than business-to-consumer (B2C) contexts. With regard to firm size, respondents covered a broad range of annual revenues, from small and medium-sized enterprises (e.g., 28% with a revenue between 1-25 Mio. Euro; 13% with a revenue between 25-250 Mio. Euro) to large corporations (≈10% with more than 2 Billion Euro revenue). In terms of organizational position, the sample was dominated by marketing managers and heads of marketing, complemented by senior executives, including managing directors and CEOs. This composition ensures that the responses largely reflect a decision-maker perspective with direct responsibility for marketing strategy and analytics.

As the study relies on a convenience sample rather than a probabilistic sampling approach, the findings are not statistically representative of the overall population of firms. Nevertheless, the sample composition and response patterns provide a meaningful snapshot of current practices and challenges in AI-based content analysis and allow for the identification of relevant trends, maturity gaps, and managerial implications.

3.2 Key Findings

Out of the total sample of 128 respondents, 111 respondents answered the question to what extend they use AI-based content analysis. Approximately half of them (n = 55; 49.5%) report using AI-based content analysis frequently or very frequently, while 56 respondents (50.5%) report lower usage frequencies (see Figure 3).

For the method-specific frequency items, 92 valid responses were available for each method. Text analysis shows the highest adoption, with 27 of 92 respondents (29.3%) reporting frequent or very frequent use. In contrast, image analysis and video analysis are each used frequently or very frequently by 9 of 92 respondents (9.8%), while multimodal analysis is reported by 10 of 92 respondents (10.9%). These results confirm that text-based approaches are currently the most established, whereas image-, video-, and multimodal methods remain considerably less common.

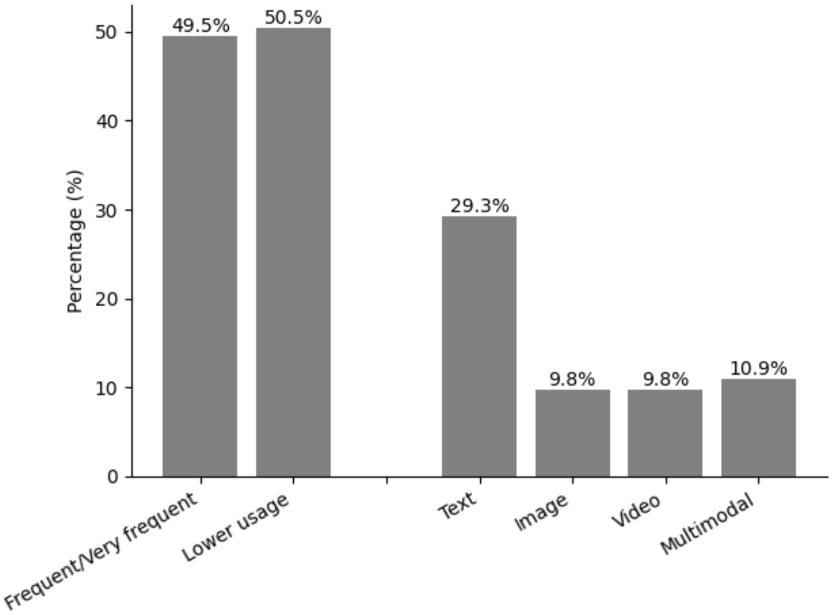

Figure 3. Use of AI-based content analysis methods (Source: own development).

The maturity level of AI-based content analysis processes remains low overall (N = 78). Process maturity shows a low central tendency (M = 2.35, Md = 2, SD = 1.05), indicating that most organizations are still at an early stage of implementation. A differentiated picture emerges across organizational capabilities (N = 78). Governance and compliance capabilities are rated higher (M = 2.77, Md = 3, SD = 1.07) as are financial resources (M = 2.72, Md = 3, SD = 1.08). In contrast, human-resource capabilities and domain-specific know-how remain comparatively limited (M = 2.49, Md = 2, SD = 1.10), highlighting a persistent skills gap. Decision integration is assessed at a moderate level. Based on 78 valid responses, the integration of AI-based insights into decision-making reaches M = 2.99 (Md = 3, SD = 1.15). Perceived outcomes are more positive than the underlying capabilities. For perceived benefits and ROI, 75 valid responses were available. Overall benefit reaches M = 3.16 (Md = 3, SD = 1.08), while ROI reaches M = 3.01 (Md = 3, SD = 1.07). This indicates that organizations already perceive tangible value from AI-based content analysis, even at relatively early stages of adoption.

In terms of applications, responses are based on 71 respondents who indicated at least one use case. Campaign optimization is the most frequently reported application, with 49 of 71 respondents (69.0%), followed by personalization and segmentation (44 of 71 respondents, 62.0%). Brand monitoring and product development are each reported by 23 of 71 respondents (32.4%), while early crisis detection remains comparatively rare, with 8 of 71 respondents (11.3%) selecting this option (see Figure 4).

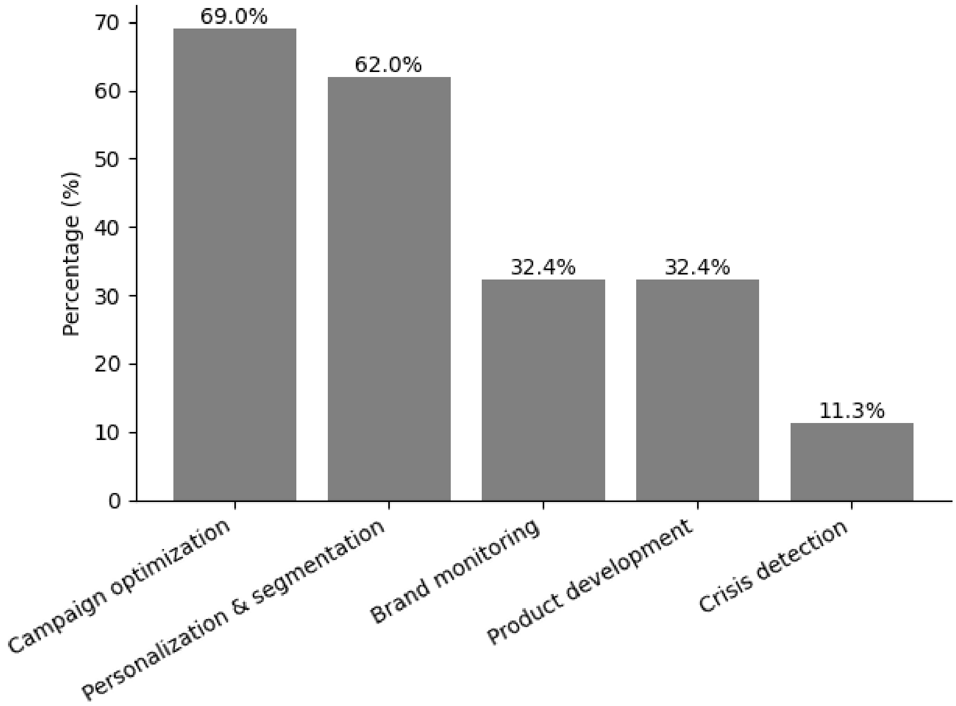

Figure 4. Goals and fields of application in AI-based content analysis (Source: own development).

Barrier perceptions remain consistently elevated. Based on N = 76, technical barriers are rated highest (M = 3.43, Md = 4, SD = 1.02), followed by organizational barriers (M = 3.32, Md = 4, SD = 1.10), legal and ethical barriers (M = 3.18, Md = 3, SD = 1.12), and explainability and acceptance issues (M = 2.82, Md = 3, SD = 1.13). These findings indicate that technical and organizational challenges are perceived as the most substantial obstacles. Future investment expectations show a moderate upward tendency. Based on 75 valid responses, budget development for AI-based content analysis in 2026 is rated at M = 3.19 (Md = 3, SD = 1.05), indicating cautious but positive investment intentions.

In addition subgroup analyses were conducted comparing users (n = 55) and non-users (n = 56). The results reveal substantial differences across key dimensions. Users exhibit higher process maturity (M = 2.74 vs. 1.89, Cohen's d = 0.87), stronger governance capabilities (M = 3.02 vs. 2.47, Cohen's d = 0.53), greater decision integration (M = 3.50 vs. 2.39, Cohen's d = 1.10), higher perceived benefits (M = 3.62 vs. 2.58, Cohen's d = 1.10), and higher perceived ROI (M = 3.38 vs. 2.55, Cohen's d = 0.84). These effect sizes indicate moderate to large differences, particularly for decision integration and perceived value.

Overall, the results confirm the process logic outlined in this study: effective AI-based content analysis requires a structured end-to-end pipeline, from goal definition to data preparation, analysis, and managerial implementation, supported by appropriate governance mechanisms. While text-based approaches are currently the most mature and widely adopted, visual and multimodal methods remain less developed. At the same time, the findings indicate a transitional phase in which perceived benefits and investment intentions already exceed the current level of organizational capabilities. Free-text responses in the survey underscore the effectiveness: mentions include massive efficiency gains in content creation and campaigns, automated competition/market overviews, significantly improved target group ROIs, and faster, data-driven decisions.

4 CONCLUSION, MANAGERIAL IMPLICATIONS AND FUTURE RESEARCH

AI-based content analysis offers considerable potential to enhance both the efficiency and effectiveness of marketing decision-making. At the same time, the empirical findings highlight persistent organizational, technical, and regulatory challenges that continue to constrain the realization of this potential.

While approximately half of the surveyed organizations report frequent use of AI-based content analysis, this usage is heavily concentrated on text-based methods, whereas image, video, and multimodal approaches remain at comparatively low adoption levels. At the same time, process maturity is predominantly low, and governance structures are only well developed in a minority of firms. These results indicate that, although AI-based content analysis is already being applied and delivers perceived benefits, its organizational embedding remains incomplete. These empirical findings are consistent with prior literature. Existing research has emphasized that firms typically adopt less complex, text-based analytical approaches before progressing toward more advanced visual and multimodal methods (e.g., Grewal et al., 2021; Peng et al., 2023). Similarly, studies on AI in marketing highlight that the realization of value depends less on algorithmic sophistication than on organizational capabilities, governance structures, and process integration (De Bruyn et al., 2020; Vlačić et al., 2021). The present findings extend this literature by empirically demonstrating that these organizational prerequisites remain underdeveloped in many firms, thereby limiting the effective exploitation of AI-based content analysis. At the same time, the results show that despite low maturity levels and significant barriers (i.e. skills, financial resources, organizational and technical constraints) a substantial share of firms already integrates analytical outputs into decision-making processes. This suggests that organizations are operating in a transitional phase, where experimentation and partial implementation coexist with structural deficits in governance and capabilities.

However, the conclusions of this study must be interpreted in light of several limitations. First, the empirical analysis is based on a non-probabilistic convenience sample of 128 respondents from German-speaking countries, which limits the generalizability of the findings beyond this context. Second, the study relies on self-reported measures of usage, maturity, benefits, and barriers, which may be subject to perceptual biases, and differences in respondents' understanding of AI-based methods. Third, the cross-sectional design does not allow for causal inferences or an assessment of how adoption and capabilities evolve over time. Finally, the measurement of key constructs (e.g., maturity, ROI, governance) is necessarily simplified and does not capture the full complexity of organizational implementation. Against this background, broader implications should be drawn with caution. Rather than suggesting a general transformation of marketing through AI-based content analysis, the findings indicate an ongoing and uneven transition in which many organizations are still building the necessary foundations for effective use. The results therefore primarily reflect the current stage of adoption among the surveyed firms rather than a fully developed or mature state of practice.

Future research could build on the present findings by addressing several specific avenues. First, longitudinal studies could examine how the adoption and organizational integration of AI-based content analysis evolve over time and which organizational capabilities drive sustained use and performance outcomes. Second, comparative research across industries could investigate how adoption patterns, use cases, and benefits differ depending on characteristics such as digitalization and data availability. Third, cross-country studies could explore how institutional environments, including regulatory frameworks and data governance regimes, influence implementation and diffusion. Fourth, future work could benchmark different AI-based content analysis approaches in terms of accuracy, interpretability, and managerial usefulness in marketing contexts. Finally, research should examine how governance mechanisms, including transparency practices, explainability tools, and ethical guidelines, shape organizational trust and responsible implementation of AI-based content analysis.

References

Baltrušaitis, T., Ahuja, C., & Morency, L.-P. (2019). Multimodal Machine Learning: A Survey and Taxonomy. IEEE Transactions on Pattern Analysis and Machine Intelligence 41(2), 423-443. https://doi.org/10.1109/TPAMI.2018.2798607

Bär, I., & Zerres, C. (2024). Social-Media-Monitoring. In: Zerres C. (Ed.), *Handbuch Social-Media-Marketing*, Springer Gabler, pp. 41-60.

Barari, M., & Eisend, M (2024) Computational content analysis in advertising research. *Journal of Advertising 53*(5), 681–699. https://doi.org/10.1080/00913367.2024.2407642

Berger, J., Humphreys, A., Ludwig, S., Moe, W.W., Netzer, O., & Schweidel, D.A. (2019). Uniting the tribes: Using text for marketing insight. *Journal of Marketing 83*(5), 1-25. https://doi.org/10.1177/0022242919873106

Chakraborty, I., Chiong, K., Dover, H., & Sudhir, K. (2024). Can AI and AI-Hybrids Detect Persuasion Skills? Salesforce Hiring with Conversational Video Interviews. *Marketing Science 44*(1), 30-53. https://doi.org/10.1287/mksc.2023.0149

De Bruyn, A., Viswanathan, V., Beh, Y.S., Brock, J.K.-U., & von Wangenheim, F. (2020). Artificial Intelligence and Marketing: Pitfalls and Opportunities. *Journal of Interactive Marketing 51*, 91-105. https://doi.org/10.1016/j.intmar.2020.04.007

Grewal, R., Gupta, S., & Hamilton, R. (2021). Marketing Insights from Multimedia Data: Text, Image, Audio, and Video. *Journal of Marketing Research 58*(6), 1025-1033. https://doi.org/10.1177/00222437211054601

Harzig, P., Brehm, S., Lienhart, R., Kaiser, C., & Schallner, R. (2018). Multimodal Image Captioning for Marketing Analysis. *IEEE Conference on Multimedia Information Processing and Retrieval*. https://doi.org/10.48550/arXiv.1802.01958

Kumar, V., Ashraf, A.R., & Nadeem, W. (2024). AI-powered marketing: What, where, and how? *International Journal of Information Management 77*, 102783. https://doi.org/10.1016/j.ijinfomgt.2024.102783

Li, H., & Zhang, N. (2024). Computer Vision Models for Image Analysis in Advertising Research. *Journal of Advertising 53*(5), 771-790. https://doi.org/10.1080/00913367.2024.2407644

Li, T., Zeng, Z., Li, Q., & Sun, S. (2024). Integrating GIN-based multimodal feature transformation and multi-feature combination voting for irony-aware cyberbullying detection. *Information Processing & Management 61*(3), 103651. https://doi.org/10.1016/j.ipm.2024.103651

Li, X., Shi, M., & Wang, X. (2019). Video mining: Measuring visual information using automatic Methods. *International Journal of Research in Marketing 36*(2), 216-231. https://doi.org/10.1016/j.ijresmar.2019.02.004

Lin, Z., Xie, J, & Li, Q. (2024). Multi-modal news event detection with external Knowledge. *Information Processing & Management 61*(3), 103697. https://doi.org/10.1016/j.ipm.2024.103697

Liu, X., Lee, Y., & Srinivasan, K. (2019). Large-scale cross-category analysis of consumer review content on sales conversion leveraging deep learning. *Journal of Marketing Research 56*(6), 918-943. https://doi.org/10.1177/0022243719866690

Mahadevkar, S.V., Khemani, B., Patil, S., Kotecha, K., Vora, D.R., & Abraham, A. (2022). A Review on Machine Learning Styles in Computer Vision - Techniques and Future

Directions. IEEE Access, 10, 107293-107329.
Mahadevkar, S.V., Patil, S., Kotecha, K., Soong, L.W., & Choudhury, T. (2024). Exploring AI-driven approaches for unstructured document analysis and future horizons. *Journal of Big Data 11*(92), 1-54. https://doi.org/10.1186/s40537-024-00948-z
Moon, S., & Kamakura, W.A. (2017). A picture is worth a thousand words: Translating product reviews into a product positioning map. *International Journal of Research in Marketing 34*(1), 265-285. https://doi.org/10.1016/j.ijresmar.2016.05.007
Mroueh, Y., Marcheret, E., & Goel, V. (2015). Deep multimodal learning for Audio-Visual Speech Recognition. 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), South Brisbane, QLD, Australia, 2130-2134.
Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science 31*(3), 521-543. https://doi.org/10.1287/mksc.1120.0713
Peng, Y., Lock, I., & Ali Salah, A. (2023). Automated Visual Analysis for the Study of Social Media Effects: Opportunities, Approaches, and Challenges. *Communication Methods and Measures 18*(2), 163-185. https://doi.org/10.1080/19312458.2023.2277956
Philp, M., Jacobson, J., & Pancer, E. (2022). Predicting social media engagement with computer vision: An examination of food marketing on Instagram. *Journal of Business Research 149*, 736-747. https://doi.org/10.1016/j.jbusres.2022.05.078
Roy, S.K., Tehrani, A.N., Pandit, A., Apostolidis, C., & Ray, S. (2025). AI-capable relationship marketing: Shaping the future of customer relationships. *Journal of Business Research 192*, 115309. https://doi.org/10.1016/j.jbusres.2025.115309
Schraml, C. (2025, May 21). Automated Video Analytics in Marketing Research: A Systematic Literature Review and a Novel Multimodal Large Language Model Method. https://doi.org/10.31219/osf.io/63nbc_v1
Vial, G. (2019). Understanding digital transformation: A review and a research Agenda. *The Journal of Strategic Information Systems 28*(2), 118-144. https://doi.org/10.1016/j.jsis.2019.01.003
Vlačić, B., Corbo, L., Costa e Silva, S., & Dabić, M. (2021). The evolving role of artificial intelligence in marketing: A review and research Agenda. *Journal of Business Research 128*, 187-203. https://doi.org/10.1016/j.jbusres.2021.01.055
Volkmar, G., Reinecke, S., & Fischer, P.M. (2021). Künstliche Intelligenz im Marketing: Möglichkeiten und Herausforderungen. *Die Unternehmung 75*(3), 359-375.
Xiao, L., Wu, X., Wu, W., Yang, J., & He, L. (2022). Multi-Channel Attentive Graph Convolutional Network with Sentiment Fusion for Multimodal Sentiment Analysis. IEEE International Conference on Acoustics, Speech and Signal Processing, Singapore, 4578-4582.
Xu, D., Chen, T., Pearce, J., Mohammadi, Z., & Pearce, P.L. (2021). Reaching audiences through travel vlogs: The perspective of involvement. *Tourism Management 86*, 104326. https://doi.org/10.1016/j.tourman.2021.104326
Yang, J., Zhang, J., & Zhang, Y. (2025). Engagement that sells: Influencer video advertising on TikTok. *Marketing Science 44*(2), 247–267. https://doi.org/10.1287/mksc.2021.0107
Zerres, C., & Israel, K. (2025). KI im Marketing in Breyer-Mayländer, T., Drechsler, D., Zerres, C. (Hrsg.), KI-Transformation in Deutschland, utb Verlag, S. 289-307.
Zhou, M., Chen, G.H., Ferreira, P., & Smith, M.D. (2021). Consumer Behavior in the Online Classroom: Using Video Analytics and Machine Learning to Understand the Consumption of Video Courseware. *Journal of Marketing Research 58*(6), 1079-1100. https://doi.org/10.1177/00222437211042013