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

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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

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

Povzetek: Eksponentna rast digitalnih vsebin je temeljito spremenila načine, kako lahko organizacije opazujejo, razumejo in napovedujejo človeška stališča ter vedenje. V marketingu in sorodnih področjih se je analiza vsebin, ki temelji na umetni inteligenci (UI), uveljavila kot ključna analitična zmogljivost za pridobivanje vpogledov iz nestrukturiranih podatkov, kot so besedila, slike, zvok in video. Čeprav so pretekle raziskave obsežno obravnavale posamezne metode, je manj znanega o tem, kako organizacije te pristope dejansko uvajajo in vključujejo v procese odločanja.
Za zapolnitev te vrzeli študija zasleduje dva cilja. Prvič, podaja strukturiran pregled metod analize vsebin, ki temeljijo na umetni inteligenci, ter predlaga celovit procesni model, ki poudarja organizacijsko integracijo in ne zgolj algoritemske učinkovitosti. Drugič, predstavlja ugotovitve empirične raziskave med marketinškimi managerji in strokovnjaki, ki preučuje uporabo, stopnjo zrelosti, cilje, zaznane koristi ter ovire, povezane z uporabo analiz vsebin na osnovi umetne inteligence v praksi.

Ključne besede: analiza vsebin na osnovi umetne inteligence; analiza besedil; analiza slik; analiza videa; multimodalna analiza
Klasifikacija JEL: L21, M15, M31

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.

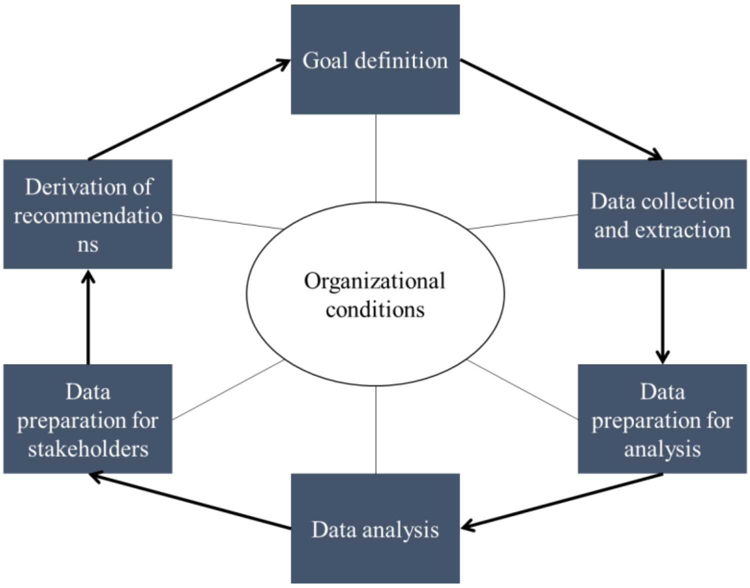

Figure 1. Process model for AI-based content analysis (Source: own development).

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).

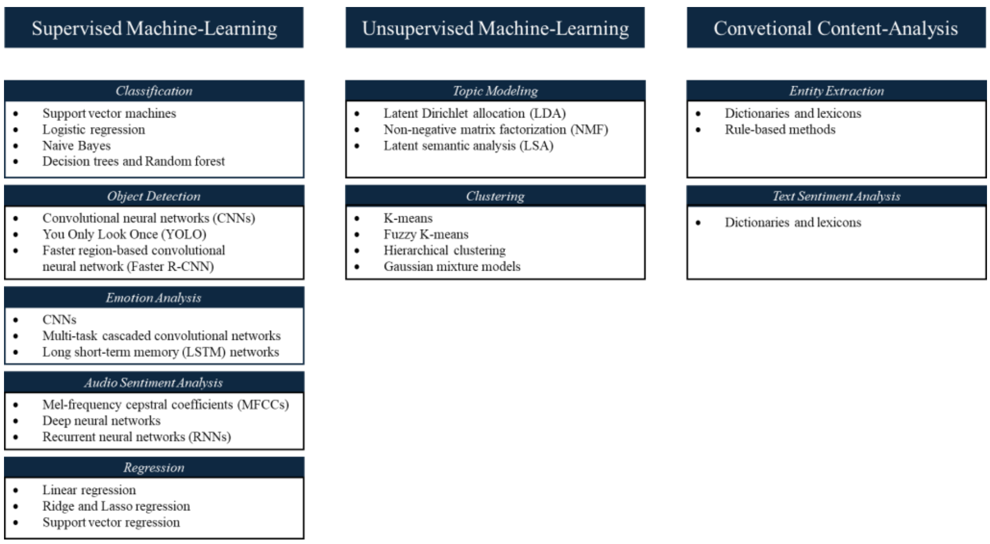

Figure 2. Systematization of AI-based content analysis methods (Source: own development based on Barari and Eisend, 2024).

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 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-4/5), 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-4 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:

- Is there a coordinated process? Is there a strategy?
- For which questions are AI-based content analysis methods used?
- Which AI-based content analysis methods are used?
- What are the reasons for not using the methods and what challenges or difficulties exist within the company?
- What are the advantages of using the methods?

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 Likert-type 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 119 were fully completed and deemed usable for analysis. 23 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

Approximately half of the respondents report using AI-based content analysis frequently or very frequently (≈49 %) (see Figure 3). Text-based methods (≈31 % often/very often) dominate the current analytical portfolio, whereas image (≈9 %), video (≈10 %), and multimodal analyses (≈12 %) are employed considerably less often. This usage pattern reflects the adoption trajectory described in prior research, which typically progresses from text-based approaches toward more complex visual and multimodal methods.

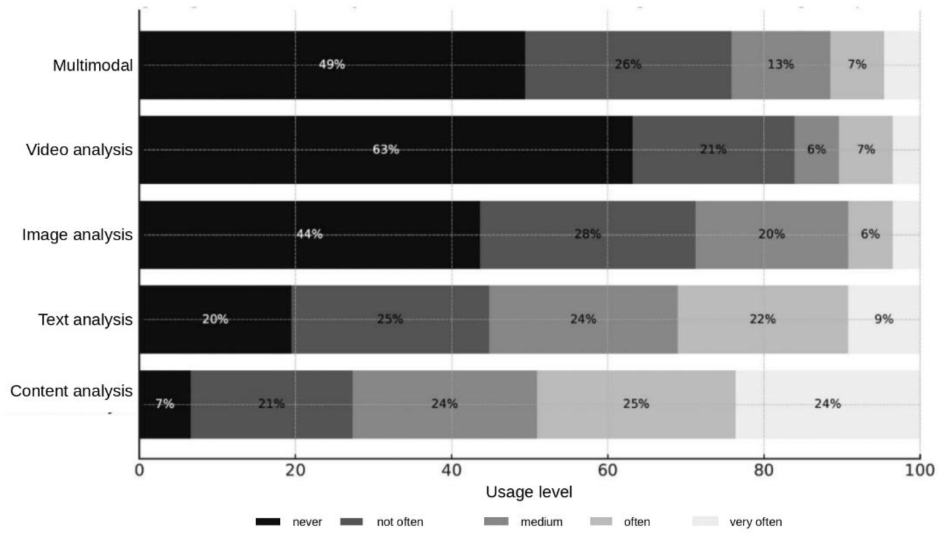

Figure 3. Use of AI-based content analysis methods (Source: own development).

The maturity level of the underlying processes is predominantly low (≈62% at the "very low"/"low" levels). This confirms the problem described in the introduction, namely that the processes in place are often inadequate in practice. Governance and compliance capabilities also only score highly in around a quarter of cases (≈26%). Bottlenecks arise primarily due to resources and skills: around 41% report low financial resources, and around 53% attest to weak HR/know-how capacities for AI-based content analyses. Nevertheless, the results are already being incorporated into decisions in a measurable way (≈36% often/always), and the overall benefits achieved are predominantly rated as medium to high (≈44%), the ROI with ≈37%. In terms of applications, campaign optimization (≈66%) and personalization and segmentation (≈60%) dominate, followed by brand monitoring and product development (≈31–33% each) and early crisis detection (≈11%) (see Figure 4).

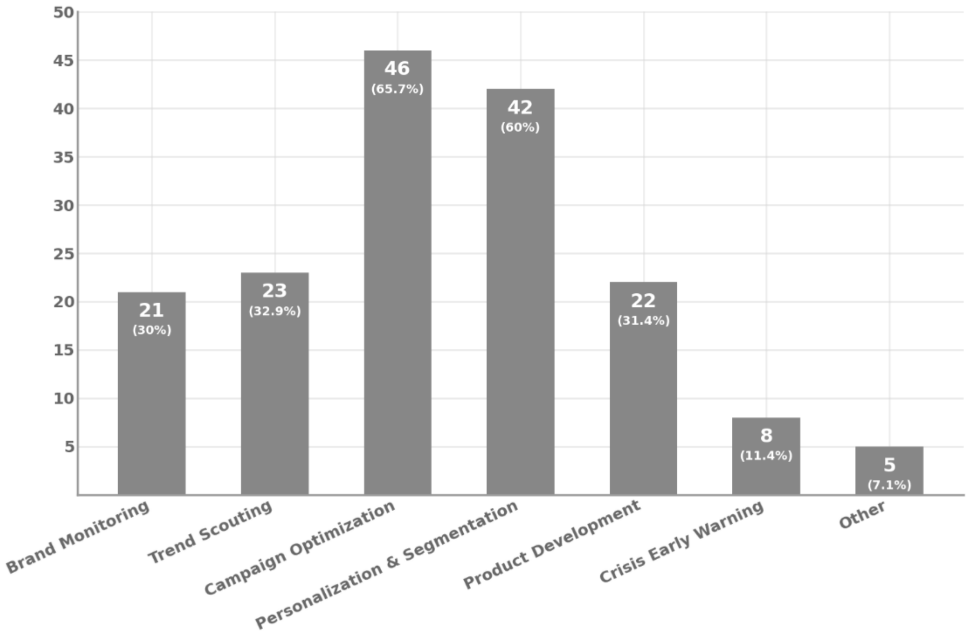

Figure 4. Goals and fields of application in AI-based content analysis (Source: own development).

The perception of obstacles is consistent across organizations: 53% rate organizational barriers as high to very high, 52% rate technical barriers as high to very high, 44% rate legal and ethical barriers as high to very high, and 28% rate explainability/acceptance as high to very high. For 2026, about one-third signal a high to very high willingness to invest (≈35%; another ≈41% moderate).

The survey confirms the process logic recommended in the article: from precise goal definition to data collection and preparation to analysis, result preparation, and derivation of measures. It is necessary to anchor this as a standardized end-to-end pipeline with integrated governance (GDPR/copyright, ethical guidelines, model transparency, bias monitoring). While text-based workflows (e.g., entity, topic, and relation extraction) are more mature, visual and multimodal methods offer the greatest additional leverage for impact and efficiency gains.

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 AND MANAGERIAL IMPLICATIONS

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.

Three central managerial implications emerge from the analysis. First, organizations should prioritize the standardization of processes and analytical architectures to ensure scalability, transparency, and consistent quality. Second, targeted capability building at the interface of marketing, information technology, and data analytics is essential. This includes clearly defined roles, focused training initiatives, and systematic monitoring of benefits and return on investment. Third, firms should develop a strategic roadmap toward multimodality, gradually extending from text-based analyses to image, video, and fully integrated multimodal approaches.

A structured and governance-aware approach to AI-based content analysis can help bridge the gap between technological potential and realized business value, thereby strengthening the role of AI-driven insights in marketing strategy and innovation.

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