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Human Creativity vs. Artificial Intelligence: An Experiment to Test User Engagement on Instagram Posts by Brands

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Introduction

The fast advancements in the field of artificial intelligence (AI) have started a movement of profound changes across fields such as culture, economy, and science. In this context, tools such as Generative AI (GenAI) and Large Language Models (LLMs) gained a lot of attention, not only as a technical innovation, but also as a cultural phenomenon. Their accessibility and ease of use have led to an increasing number of people incorporating them into their everyday lives.

For companies, this possibility opens new doors and changes how they interact with customers and make strategic decisions about how to proceed (Dwivedi et al., 2024, p. 2). In addition to regular AI, which is able to make predictions, GenAI can create new content based on learned data patterns (Grewal et al., 2025, p. 704). This support increases efficiency and saves time, automates various processes and gives employees the chance to focus on different tasks (McKinsey & Company, 2023). One of these GenAI-tools is ChatGPT. ChatGPT earned significant attraction and is among the most used AI-models (Grewal et al., 2025, p. 705) and due to the widespread accessibility of such tools, the exploration of creative and content-related applications has accelerated (Grewal et al., 2025, p. 705; Feuerriegel et al., 2023, p. 111).

Content creation is highly relevant for social media, a field that revolutionized the way brands interact with new potential and existing customers by allowing real-time conversation worldwide (Kaplan & Haenlein, 2010, p. 61). By implementing a strategic approach, companies can increase engagement, brand loyalty, as well as purchase intentions of consumers (Ahmad et al., 2016, p. 333). To achieve this, appropriate content is required, which, at best, sparks user interaction with the content published by a brand. This interaction can be measured using engagement metrics, such as likes, comments or shares.

Content on social media can be categorized into different types and thus, satisfy different needs. These types all elicit different levels of user engagement. Even though entertainment and informativeness are dominant motivators of social media use, informative content has been perceived as less engaging, whereas entertaining content has shown to enhance user engagement, especially if it provides a hedonic value (Muntinga et al., 2011, p. 27; de Vries et al., 2012, p. 85; Tellis et al., 2019, pp. 1, 11). As user engagement plays a crucial role in social media marketing (SMM), professionals are constantly looking for ways to improve their approach. With the rise of AI, an increasing number of people rely on AI for support in different areas. Findings on the effect of AI-created content (ACC) on user reactions are mixed. While positive effects like enhanced creativity and thus improved engagement intentions, have been attributed to AI (Gu et al., 2024, p. 2230), problems like lack of authenticity or sincerity have also been reported (Jung et al., 2025, pp. 4-5). Therefore, the increased use of AI on brand communication of social media and the mixed findings of prior research raise questions and concerns about how aspects such as trust, brand authenticity or user reactions in general are affected by the incorporation of AI for content creation (Lanfranchi et al., 2025, p. 15).

As users are active in their choice of media, the selection of what to consume is made based on specific needs, according to the uses and gratification theory (U&G) (Katz et al., 1973b, p. 165). If social media content satisfies users' needs, their engagement on posts can be interpreted as evidence of the sought gratifications being obtained (Ruggiero, 2000, p. 19). Commitment and trust, as defined in the commitment-trust theory by Morgan and Hunt (1994), are to factors that play an important role in establishing a relationship between a brand and an individual, since they encourage cooperation (p. 22). Another highly relevant construct that needs to be considered in this context is brand authenticity. It consists of six factors, all of which need to be upheld to appear authentic: accuracy, connectedness, integrity, legitimacy, originality, and proficiency (Nunes et al., 2021, p. 2). Authenticity is essential to establish trust and a solid relationship, which ultimately increases loyalty and engagement (Nunes et al., 2021, p. 3). In order to be perceived as authentic and keep up trust, inconsistent brand behavior and sudden stylistic shifts should be avoided (Schallehn et al., 2014, p. 192).

The number of studies examining how the implementation of AI in content creation affects user reactions is continuously growing. Previous studies have shown that the explicit disclosure of AI-use lowered trust and authenticity (Brüns & Meißner, 2024, p. 5). Conversely, if this disclosure was not provided, ACC could even outperform human-created content (HCC) in terms of social media engagement (Aldous et al., 2024, pp. 379-380). Additionally, it seems that contextual factors such as tone of voice and stylistic choices can play a more important role than the content source itself, as users often are not able to reliably distinguish between ACC and HCC (Oh & Ki, 2024, p. 6; Jakesch et al., 2023, p. 1). The mixed and context-dependent results, combined with the fact that existing studies were only conducted in controlled settings, highlight the need for research conducted in real-world environments.

While AI is increasingly used in marketing, to the best of current knowledge, at this moment no research on how brand communication created by AI performs in a real-life social media context has been conducted. To fill this gap and examine this aspect, the overarching research question was stated as follows: How does AI-created content (ACC) affect user engagement compared with human-created content (HCC) on a real brand's Instagram channel? This study was based on three theoretical foundations. Firstly, the uses and gratifications theory by Katz et al. (1973a), which explains why individuals choose certain media and interact with specific content. Secondly, the commitment-trust theory by Morgan and Hunt (1994) emphasizes the importance of trust and commitment in establishing long-term relationships with customers. Thirdly, authenticity provides additional insight into the importance of being perceived as genuine and trustworthy, which is crucial for establishing credibility and fostering strong relationships with customers.

To answer the research question, a field experiment was conducted on a real brand account on Instagram in order to capture user reactions in an authentic application context. In collaboration with Leica Camera Classics, 42 posts were published on the brands Instagram account. Half of the posts were accompanied by a caption written by ChatGPT4-o, lightly edited once if needed, while the other half was written by a human writer. To gain more nuanced insight into how different content sources affect user engagement across different content types, published posts were categorized as informative, entertaining or promotional. As the study follows a quantitative design, engagement metrics, likes, comments, shares, views and saves, were collected one week after each post was published, to ensure an objective analysis of user reactions.

The structure of the thesis is as follows: First, the conceptual background of AI is provided, covering all relevant definitions and connections between different constructs, such as AI, GenAI, LLMs. The subsequent chapter gives an overview of the literature on social media and related aspects. The following chapter connects the previous topic of GenAI with social media marketing. The theoretical foundations, which formed the basis of this study, as well as relevant previous studies are presented, followed by the research questions and hypothesis of this study. The methods chapter provides detailed insight into how this study was conducted, which variables were included and other relevant information and covers the methodological approach, while the following chapter presents the results of this study. In the last chapters, the findings are discussed, implications for future research are derived and limitations and outlook are formulated. This study aims to provide relevant contributions to the field of AI-supported brand communication on social media and how it affects user engagement, as this topic is not only scientifically relevant, but also highly current and practical.

Conceptual background

The Foundations of Artificial Intelligence

The concept of AI has been researched in many contexts, such as psychology, mathematics or philosophy, linguistics and computer science, but not all components that came from these fields aimed at creating AI as their ultimate goal (Russell & Norvig, 1995, p. 8). Even though philosophical concepts of AI had existed earlier (Nilsson, 2010, p. 56) and researchers had been working on the concrete concept for about five years, its formal introduction can be traced back to 1956, when it was introduced for the first time during a summer school at Dartmouth College in New Hampshire, USA (Sheikh et al., 2023, p. 3, 28). While AI has been in circulation in our world for decades, scholars have been struggling to come up with a comprehensive definition of AI that is fitting for its many facets (Russell & Norvig, 1995, p. 29). Considering the complexity and versatility of intelligence, it is challenging to create a definition that incorporates all different aspects (Wang, 2019, p. 1). In a rather recent perspective, Sheikh et al. (2023) defined AI as "systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals" (p. 19). Russell and Norvig (1995) divided definitions of AI along two main dimensions: whether the system aims to think or act, and if it imitates human performance or acts rationally (p. 4). This leads to the following four paradigms: acting humanly, thinking humanly, acting rationally, and thinking rationally, all of which follow different goals (Table 1) (Russel and Norvig, 1995, p. 4).

Table 1

Four paradigms of AI definitions

Thinking humanly	**Thinking rationally**
Goal: Understanding and replicating human thought processes	Goal: Logically correct reasoning
Acting humanly	**Acting rationally**
Goal: Acting like a human	Goal: Making optimal decisions in a given context

Note. Based on Russell and Norvig (1995, pp. 4-8).

For the dimension of "acting humanly", the Turing Test was established by Alan Turing in 1950, because an operational definition of intelligence was needed (Russell & Norvig, 1995, p. 5). To pass the test, a computer needs to be capable of NLP, knowledge representation, automated reasoning, and machine learning (ML) (Russell & Norvig, 1995, p. 5). For an extended period of time, no big efforts were made to pass the test in the field of AI (Russell & Norvig, 1995, p. 6).

Even though AI tools have proven to be useful and have advanced a lot, without really understanding how they work, people should be cautious in how they use them (Sheikh et al., 2023, p. 75). From an outside perspective it is often challenging to comprehend how AI makes decisions and even though the process might be revealed, it does not mean that it can be explained (Sheikh et al., 2023, p. 75). To avoid automation bias, which means that humans tend to rely on automated systems too heavily (Abdelwanis et al., 2024, p. 460), users must remain cautious and should not trust AI blindly. Networks like AI are powerful because they can learn with training sets of data and the associated right answers and thus improve and strengthen networks to a point where, if they get new data, they can classify it, even if it is previously unknown (Castelvecchi, 2016, p.22). These observations support a central point: while AI can produce accurate output, the underlying mechanisms which determine the performed action are not transparent to users. To gain a better understanding of how and why AI systems can learn, apply patterns and sometimes fail, it is important to have a sufficient understanding of the subfields on which they are built. ML and DL form the backbone of many AI systems. Therefore, the next chapter introduces these subareas and explains how they gain knowledge from data and why this influences their strengths and limitations.

Subfields of AI: Machine learning, Deep Learning and Natural Language Processing

There are five types of AI, (a) ML, (b) computer vision, (c) NLP, (d) speech recognition, and (e) robotics (Sheikh et al., 2023, p. 50). The most commonly used one is ML (Sheikh et al., 2023, p. 50), which is often confused with AI, and whose terminology is frequently used interchangeably (Kühl et al., 2022, p. 2). Clarifying the differences between the concepts is essential to understand how contemporary AI tools work. In the context of AI, ML is a subfield of AI (Seeger, 2024, p. 33), which refers to the use of certain attributes, which can be studied to identify patterns, that in turn can be applied to similar situations in the future (Kaul et al., 2020, p. 808; Nilsson, 2009, p. 495).

ML consists of a two-step process: training and inference (Kelleher, 2019, p. 12). During training, the ML algorithm processes data and then determines a function that best matches the patterns in the data (Kelleher, 2019, p. 12). Next, this function is saved in a computer program, for example as parameters of „if-then-else rules” (Kelleher, 2019, p. 12). After training is completed, a final model is returned to the algorithm, which can then be applied to future scenarios as the second step, which is inference (Kelleher, 2019, p. 14).

Even though the correct output variable is unknown in new examples, the model is able to come up with an estimate of the value (Kelleher, 2019, p. 14). For a long time, ML was viewed as a peripheral topic, but due to the emergence of databased systems and growing capacities in data storage and increasing computational power, the focus has shifted (Nilsson, 2010, p. 495). Looking a step further, deep learning (DL) is a subarea of ML (Kelleher, 2019, p. 1).

DL concentrates on the creation and use of large neural network models that allow decisions that are based on data and are especially suited for tasks with complex structures and a large amount of data (Kelleher, 2019, p. 1). The majority of online companies and high-end consumer technologies use DL, for example Facebook, where it is used to analyze text in conversations (Kelleher, 2019, p. 1). Furthermore, smartphones have integrated DL systems such as speech recognition or face detection (Kelleher, 2019, p. 1).

As previously stated, NLP emerged around 1950 and referred to an intersection between AI and linguistics, while nowadays it requires interdisciplinary knowledge from researchers, as it is connected to many different fields (Nadkarni et al., 2011, p. 544). During the 1980s, there was a shift from manually defined rules to a database approach. This change marked the emergence of machine-learning methods that utilized probabilities, thereby initiating the beginning of statistical NLP (Nadkarni et al., 2011, p. 545), which is a premise for the rise of modern LLMs.

Together, ML, DL, and NLP form the technological foundations of current GenAI-systems and illustrate how AI has grown into a highly sophisticated tool with capabilities to process large amounts of data, often within seconds. These subfields support the core mechanisms of LLMs, which extend beyond mere prediction toward the generation of text, images, and more.

Applications of AI: Generative AI and Large Language Models

Recent developments in AI have expanded its range of application, transforming it from a traditional analytical tool into a central driver of innovation across various fields. For years, it was assumed, that only humans were able to carry out tasks that required creativity - a belief, that has been refuted due to the fast developments in this field of AI, which have made it possible to produce new content where the source cannot be clearly identified (Feuerriegel et al., 2023, p. 111). One of these systems is GenAI. It can be defined as “computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data.” (Feuerriegel et al., 2023, p. 111). These programs can fulfill a variety of tasks, from creating new content to supporting humans, providing intelligent answers (Feuerriegel et al., 2023, p. 111). They produce this new content by studying patterns from the data used to train them (Sengar et al., 2025, p. 23662), and ultimately, their output depends on the prompts they are given by users (Banh &Strobel, 2023, p. 1).

GenAI exists in many different types, one of which are so-called "transformers" (Sengar et al., 2025, p.23665), introduced by Vaswani et al. (2017). "Transformers" revolutionized AI, by enabling models capable of tasks like translation or text generation (Sengar, 2025, p. 23667). With them came a key innovation - attention mechanisms - which made it possible to for the models to understand the relationships between words, independent of their position in a sequence (Sengar, 2025, p. 23667). Being based on transformer architecture and being built around these self-attention mechanisms, enables parallelization and gives them the ability to efficiently handle long-range dependencies (Raiaan et al., 2024, p. 26840). Therefore, „transformers" have the ability to effectively learn complex language patterns, which made them the basis for GenAI-models like Open AI's Generative Pre- trained Transformer (GPT) and Google's Bidirectional Encoder Representations from Transformers (BERT) (Sengar, 2025, p. 23667).

While GenAI relies on analytical AI as a foundation, the difference is that it creates new content based on already existing data and content, rather than solely predicting outcomes based on past data (Grewal et al., 2025, pp. 703-704). For example, this means that where analytical AI predicts the optimal next-offer or which leads should be focused on, Gen AI can create product descriptions for said offers or write sales scripts and act as a sparring partner in preparation for pursuing these identified leads (Grewal et al., 2025, p. 704).

Thus, GenAI represents an extension of traditional AI, shifting the focus from predicting to creating, which offers new possibilities across various industries. In marketing, for instance, every element of a marketing strategy, as well as each phase of planning the strategy, can be impacted by GenAI (Grewal et al., 2025, p. 704). With steady improvements and new possibilities, it is transforming the way marketeers work, from content creation to customer interaction, as well as market research or strategy development (Grewal et al., 2025, p. 702). Leading companies like Walmart or Emirates NBD bank were able to increase success by utilizing GenAI for different tasks, such as creating personalized ad copies or even creating chatbots that take over negotiations with vendors (Grewal et al., 2025, p. 702). This emphasizes how GenAI can increase efficiency and creativity at the same time, which provides companies with both strategic and operational benefits.

Further examples of GenAI applications include the writing assistant “Grammarly” or the currently most used form of GenAI, ChatGPT (Grewal et al., 2025, p. 705). Another benefit of GenAI is that certain GenAI solutions can be used by businesses immediately, regardless of the data structure of the company (Grewal et al., 2025, p. 705), which again saves time and often does not require a high level of expertise.

As the integration of AI, more specifically GenAI, in businesses increases, the question of whether it actually brings advantages gains relevance. Therefore, studies have been investigating the effects and gaining more insight into how these solutions are applied. When senior executives were asked about how they would judge their way of implementing GenAI so far, successes like reduced workload for retail store employees, leading to a reduction of labor time and costs, and a significant increase of sales after implementing GenAI, were reported (Grewal et al., 2025, p. 710).

Whether human augmentation, meaning a check and, if needed, modification before something is presented to the final customer, should be applied or not on output created by GenAI, needs to be carefully considered in each company. Many companies tend to combine the efficiency of AI with human checkups to ensure accuracy, appropriateness, and data protection are given (Grewal et al., 2025, p. 710).

When analyzing research in the field of GenAI, it is still new and needs to be continued to gain further insight, but clear advantages like increasing efficiency or coming up with new ideas are documented (Grewal et al., 2025, p. 711). Simultaneously, research shows that wrong or inappropriate content, whether from hallucinations (Huang et al., 2025, p. 1) or biases, can occur. Therefore, a certain level of human augmentation should be applied to the output, to ensure accuracy and ethical standards, which also emphasizes the urgent need for further empirical research in the marketing context (Grewal et al., 2025, p. 711).

One type of the aforementioned „transformers” are LLMs, which are therefore also based on a self-attention mechanism, that allows them to process relationships between words, regardless of their position. They are a specific type of GenAI, which is focused on producing text and language-based content and try to mimic human behaviors in regard to language processing (Cascella et al., 2023, p.32). When looking at the history of NLP, it commenced with statistical language modeling (LM), which then developed into neural LM, followed by pre-trained language models (PLMs) and ultimately LLMs (Naveed et al., 2025, p. 2). In recent years, LLMs have revolutionized the field of AI (Sarker, 2024, p.1). Through constant development of the model, scaling, and the continuous expansion of training data, LLMs have progressively improved in areas such as generalizability, reasoning, planning, and making decisions (Naveed et al., 2025, p. 2). Research has shown that all layers within LLMs, from the lowest to the highest, contribute similarly to the improvement of prediction abilities, regardless of the models design or training data (He & Su, 2025, p. 1). Furthermore, inappropriate, or incorrect behavior is being increasingly reduced through fine-tuning task instructions and alignment with human feedback. (Naveed et al., 2025, p. 2).

Most of the time LLMs contain around a minimum of ten billion parameters (Campesato, 2024, p. 38) and are trained using huge text datasets from the internet, allowing them to understand complex meanings and structures of language, which, combined with DL, allows them to perform tasks such as translations, sentiment analysis, or summaries (Raiaan et al., 2024, p. 26840). Still, even though LLMs constantly improve, the question of how trustworthy they are, arises (Huang et al., 2024, p. 2) and, in addition to potential misuse of these tools (Sadasivan et al., 2023, p. 1), excessively relying on GenAI or LLMs can hinder the development of skills such as creativity, critical thinking, and problem solving, depending on how they are used (Iskender, 2023, p. 3).

These advancements highlight the technological capabilities and the transformational potential of GenAI. As one of the most used programs, ChatGPT exemplifies how applications based on LLMs work in practice, and thus, poses as a central example of today's understanding of the use of AI.

ChatGPT

As AI-tools and LLMs are becoming more prominent in daily life, among the most commonly used are models from GPT series (Grewal et al., 2025, p. 705). ChatGPT is considered to be the first LLM that commenced a more modern era of LLMs and has since been succeeded by newer versions such as ChatGPT-4o (Campesato, 2024, p. 55). ChatGPT is a model trained on the basis of Reinforcement Learning from Human Feedback (RLHF) (OpenAI, 2022). RLHF is a procedure, that aims to reduce the discrepancy between the statistical prediction of text and what human users actually expect, by providing the models with actual human feedback (Ouyang et al., 2022, p.2). The models are trained through ML using data from the internet, which ensures constant improvement (Pavlik, 2023, p. 85). ChatGPT was made available to the public only in November 2022 (Teubner et al., 2023, p. 96) but reached around 100 million active monthly users by February 2023 (Reuters, 2023). This growth made it the fastest growing consumer app in history. With several new features and improvements in a rather short period, in August 2024, less than two years after its first introduction to the public, the model reportedly reached approximately 200 million active weekly users (Search Engine Journal, 2024).

ChatGPT is specialized in conversing and producing human-like output, which is possible due to its deep knowledge and extensive training data (Fui-Hoon Nah et al., 2023, p. 277). ChatGPT-3 as well as GPT-4 are based on GenAI and are, due to their transformer structure, especially capable of managing data sequences and creating output, that is useful for different tasks, particularly those involving text (Campesato, 2024, p.12). Therefore, in recent years, GenAI has received increased attention in many fields, such as science and the economy, as well as marketing. Since ChatGPT is very self-explanatory to use and can support tasks like content creation, it has strongly impacted the industry (Fui-Hoon Nah et al., 2023, p. 282). It is necessary to create carefully considered prompts, in order to achieve the desired output from GenAI. In the context of marketing, the tool can be used to create synthetic, as well as personalized ads (Fui-Hoon Nah et al., 2023), where „synthetic" refers to media that have been artificially produced, manipulated or modified through AI (p. 282; Arango et al., 2023, p. 486).

While providing new opportunities and ways to creatively express oneself, tools like ChatGPT also open questions regarding authorship (Haque & Li, 2025, p. 792). Furthermore, biases of the model, depending on the composition of training data, can lead to false or distorted output (Haque & Li, 2025, p.792), as well as glitches in the system (McGee, 2023, p. 1).

While AI-tools like ChatGPT constantly take on new and more complex tasks and create output that is used for different purposes, there is a central question that needs to be considered: How is this ACC perceived from an outside perspective? Even though ChatGPT-4 has shown to have a better result than the majority of humans in a verbal IQ test, it failed the Turing Test nine out of ten times, as interrogators were able to identify AI-created output compared to human-created output (Echavarria, 2025, p. 7). This highlights that, though rapid advances have been made it this field, a certain recognizability remains. But are the traits of ACC obvious enough that they would make regular consumers suspicious and even if, how would that affect their reaction toward a brand? Gaining a better understanding of this issue is crucial, since ACC increasingly appears in contexts of brand interactions or digital communication. Therefore, fields where such content circulates, especially social media, need to be examined.

Social Media

In the last two decades, social media has grown from a „just-for-fun" platform where users shared pictures from their latest holiday into an integral part of everyday life. It has become a staple in our society and shapes how social connections are formed. With people often spending several hours a day on social media, its growing importance is clear (Agarwal et al., 2022, p. 4). Kaplan and Haenlein (2010) defined social media as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content" (p. 61). Simplified, all forms of online media that encourage people to engage, communicate and connect with others can be categorized as social media (Saravanakumar & SuganthaLakshmi, 2012, p. 4444). These applications allow users to be in contact with others from all over the world, give individuals the opportunity to make themselves heard and share insights into their private life. By posting opinions, photos, or other content, as well as exchanging messages with others, users keep social media - independent and commercial virtual social networks - alive (Armstrong & Kotler, 2023, p. 480).

Social media platforms comprise different categories, such as social networking sites, sites to share photos or videos, business networking sites, micro blogging sites and many other ones (Whiting & Williams, 2013, p. 363). Concrete examples include Instagram, Facebook, Snapchat, X, TikTok or LinkedIn.

Communication among individuals, as well as brand communication has been drastically revolutionized. Today, at very low costs, companies can get in contact with people from all over the world, which significantly increases the potential customer base for certain services and offers. Simultaneously, it allows users to engage with a brand and show their support. However, this growing interactivity comes with challenges. Social media has greatly impacted how people transmit word-of-mouth (WOM). Especially negative WOM (NWOM) can have strong negative effects on the image of a brand, as well as customers' purchase intentions (Balaji et al., 2016, p. 528). NWOM refers to the sharing of negative opinions or feedback by a customer with people in their surroundings (Balaji et al., 2016, p. 529). Compared to classical WOM, electronic WOM and especially social WOM spread significantly faster and reach a significantly larger number of users (Balaji et al., 2016, p. 529). Considering the rapid dissemination of negative news or reviews on social media, it is crucial for brands to be careful and attentive to all content they publish on these platforms (Saravanakumar & SuganthaLakshmi, 2012, p. 4444). If negative reviews or comments go viral, meaning they are shared by a massive number of users, it can have detrimental effects on a company, going as far as a public relations crisis (Daugherty & Hoffman, 2014, p. 83).

All in all, social media enables targeted and personalized output, cost-effective, real-time communication with individual users or groups. However, it is a user-controlled medium, which always bears the risk of campaigns or output in general backfiring, if it is received negatively (Armstrong & Kotler, 2023, pp. 480-487).

It has become essential for brands to have a strong and well-strategized online presence, in order to keep up with today's incredibly fast changing digital world (Saravanakumar & SuganthaLakshmi, 2012, p. 4444). A study by Perrin from 2015 showed that already then, 90% of young adults between the ages of 18 to 29 used social media (p.3). A strong and well thought out social media strategy is important in order to prevent low engagement rates and increased opportunities for growth (Agarwal et al., 2022, p. 1). The central role of social media platforms in shaping user interaction with others as well as brands, emphasizes how important it is for companies to strategically leverage these environments to be visible to a broad audience of potential new and existing customers, create engagement and establish long term relationships. All these aspects are directly addressed within social media marketing.

Content Marketing in the Context of Digital and Social Media

With the technical advancements and their embedding into everyday life, marketing has expanded far beyond its traditional techniques. This offers the opportunity to reach increasingly connected customers through a range of diverse channels. One of these fields, a subarea of marketing, is digital marketing, which refers to the use of digital channels, platforms, and different technologies to showcase and promote services and products, etc. to a certain target audience (Islam et al., 2024, p.1). This includes all digital channels from websites, social media, search engine optimization (SEO), emails, etc. Among them, social media has become the most powerful platform for advertising worldwide (Schmidt & Iyer, 2015, p. 433). Digital marketing has become an important tool to promote business, as it has become one of the most used sales channels (Oklander et al., 2024, p. 99). Social media marketing, a crucial part of this channel, only considers social platforms.

Over the course of the last years, social media has evolved from a pure communication platform to a central instrument in establishing a brand and has become a key component of modern marketing strategies (Ahmad et al., 2016, p. 332). It allows brands to communicate directly with consumers and thus establish relationships that go beyond traditional advertising. By changing the approach of communication from one to many to one to one, consumers are invited to join the conversation and directly engage with companies (Hewett et al., 2016, p. 1).

At the center of social media marketing is content - without high quality content it is impossible to create successful brand communication (Ahmad et al., 2016, p. 332). Content marketing (CM) refers to "the marketing and business process for creating and distributing valuable and compelling content to attract, acquire, and engage a clearly defined and understood target audience – with the objective of driving profitable customer action" (Pulizzi, 2014, p. 5). CM strategies have evolved over time (Beard et al., 2021, p. 153). While early CM took place offline (e.g. oral), the modern approach relies on online media (Beard et al., 2021, p. 153). Therefore, digital content marketing (DCM) refers to the marketing and communication of content online, which means that bit-based content is shared only through electronic channels (Koiso-Kanttila, 2004, p.46). More specifically, it includes creating, communicating, distributing and exchanging content which has added value for both brands and customers (Holliman & Rowley, 2014, p. 287). CM aims to increase market share by publishing valuable and relevant content (Ahmad et al., 2016, p. 331).

Through content that represents a company, users are inspired to engage with a brand and establish a relationship, which in turn motivates them to buy a product (Ansari et al., 2019, p. 5). To increase likelihood of this outcome, several success factors that contribute to the effectiveness of content have been identified in existing literature and are summarized in Table 2.

Table 2

Success factors of effective content

Factor of success	Benefit
Content quality	High quality content increases customer revisit rate and thus brand health (Ahmad et al., 2016, p. 334)
Adequacy and Appropriateness	These factors are essential for establishing trust on online platforms (Seyyedamiri & Tajrobehkar, 2019, p. 86).
Measurability	Defining key performance indicators (KPIs) makes efforts measurable and allows improved understanding of which content delivers intended results (Trunfio & Rossi, 2021, p. 268).

Interactivity	Including questions and surveys in posts increases engagement rates on social media (Liu-Thompkins, 2012, p. 1).
Creativity	Appealing content gives users a reason to regularly visit brands channels (Ahmad et al., 2016, p. 334).
Relevance	Content should be tailored to information needs and interest of target groups to increase engagement (Clark et al., 2017, p. 47).
Topicality	Content should be „up-to-date" in order to increase awareness and demand on the long run (Seyyedamiri & Tajrobehkar, 2019, p. 78).
Accuracy	Accurate content is crucial to build up customer trust (Seyyedamiri & Tajrobehkar, 2019, p. 85).

Note. This table summarizes a literature-based collection of success factors in digital CM. KPI = Key Performance Indicator.

To summarize, successful CM not only depends on factors such as creativity or relevance, but on a variety of other aspects as well. If marketers consider all aspects, it enables them to strategically plan, evaluate, and adapt their content to achieve long-term engagement and brand loyalty.

DCM can affect consumers on three different levels of engagement: emotional, cognitive, and behavioral (Hollebeek & Macky, 2019, p. 32). Emotional DCM engagement refers to the level of positive affect connected to a brand while interacting with DCM (Hollebeek & Macky, 2019, pp. 32-33; Hollebeek et al., 2014, p. 154). The thought and mental processes tied to the DCM interaction are considered as cognitive, while the effort and time actively invested in a brand reflect the behavioral DCM engagement (Hollebeek & Macky, 2019, pp. 32-34; Hollebeek et al., 2014, p. 154).

Research from Ansari et al. (2019) found a moderate but significant correlation between social media content marketing and consumer purchase decisions, as well as a positive significant connection to brand awareness (p. 9). This indicates that strategically designed content can be a driver of conversion. Furthermore, social media content marketing is a decisive factor in brand health, because it gives users the possibility to gather information about a brand and establish a relationship (Ahmad et al., 2016, p. 333). Brand health is determined by the judgment of users about the brand and the products and can be measured by metrics such as time on site and return rate of users or likes and abonnements (Ahmad et al., 2016, p. 331).

On Instagram, content includes not only the photo or video of a post, but also the caption. The accompanying captions play an important role and can significantly increase user engagement on social media (Gkikas et al., 2022, p. 7). Not only do they provide context to the visual, but they also guide how the user interprets the post (Jones & Lee, 2023, p. 103). Readability of captions needs to be considered when writing social media captions. It is essential, because it includes all elements which determine how easy a text is to understand, how fast it can be read and how interesting it is for the reader (Jian et al., 2022, p. 2). Davis et al. (2019) found that captions with high readability increased user engagement for less hedonic brands, whereas brands identified as more hedonic showed that captions that were more challenging to read received higher user engagement (p. 150). Moreover, unfamiliar words in texts can have a negative effect on user engagement (McShane et al., 2019, p. 11). The caption length also plays a significant role in user engagement. Captions longer than 125 characters are automatically partially hidden on Instagram posts and users need to tap on "more" to read the full caption. Zhang and Su (2023) found that the length of the caption was negatively related to the received likes on posts (p. 1101). Although the visual might have a strong effect on engagement on Instagram, captions remain highly relevant and still influence user reactions and engagement.

It is clear that a successful brand appearance on social media not only depends on the strategic use of the platforms, but also on the characteristics and the quality of the content itself. Consequently, it is important to understand the different forms that social media content can take, in order to accurately analyze how users respond to the output. in the digital environment.

Content Types

Social media is characterized by a constant stream of different types of content. Posts can appear in different formats, such as text, video, pictures or combinations of various types with different goals. In social media and digital marketing research, content is frequently divided into three different main types: transactional/commercial/promotional, emotional, and informative (Tellis et al., 2019, p. 4; Meire et al., 2019, p. 25). In contrast, Dolan et al. (2016) propose a categorization based on the level of specific features in content, consisting of four main categories, which are (a) level of information; (b) entertainment; (c) remunerative; and (d) relational content (p. 263). These categories, which are grounded in the uses and gratifications theory (Katz et al., 1973a) and were adapted by Dolan et al. (2016), reflect the multidimensional nature of social media communication. It is essential to classify content, as prior research showed that different content types affect user reactions and engagement differently (de Vries et al., 2012, p. 85; Tellis et al., 2019, pp. 1, 11). Although previous academic literature provides different approaches to categorize content, three content types emerge consistently as particularly relevant: informative, entertaining, and promotional content. These categories are frequently studied within research in this field and therefore, form the conceptual foundation of the following sections.

Muntinga et al (2011) found in their study about consumers' online brand-related activities (COBRAs) that gathering information is among the most important drivers for users to look at brands online (p. 27). They identified four different sub-motives: (a) surveillance; (b) knowledge; (c) pre-purchase information; and (d) inspiration (p. 27). Surveillance refers to the need to always be informed about relevant news in the social and brand-related environment (p. 27). Knowledge involves establishing expertise about brands and their products or services, and pre-purchase information includes reading reviews and other peoples' experiences about a product, in order to make informed buying choices (p. 27). Lastly, users may consume brand-related content to gather new ideas for consumption and use, which falls into the category of inspiration (p. 28). In this context, prior research showed that the perceived value of information is one of the main motivations for users to engage with content (Sánchez-Fernández & Jiménez-Castillo, 2021, p. 1124), to be active in online communities (Dholakia et al., 2004, p. 244) and to inform themselves about a company (Muntinga et al., 2011, p. 27). Therefore, informative content needs to satisfy consumers' need for information (Krowinska & Dineva, 2025, p. 1034) and refers to social media posts that include information about the brand, the product or the industry (Davis et al., 2014, p. 471). This kind of content plays a strong role in supporting users in solving problems and during the decision-making process by offering help and guiding them when interacting with a brand (Davis et al., 2014, p. 471). Therefore, brands can use this to their advantage and give users a reason to follow them online.

Informative content is generally characterized by verbal richness and generally includes facts about topics related to the brand (Tellis et al., 2019, p. 4). Additionally, informative content can be described using attributes such as intelligent, informative, useful, resourceful, helpful, and knowledgeable (Chen et al., 2002, pp. 36-37). Chen et al (2002) demonstrated in a seminal study that informativeness consistently emerged as the strongest predictor of users' general attitude toward a website (p. 40). This emphasizes that informativeness is a necessary aspect to achieve favorable consumer attitudes in digital environments. However, Tellis et al. (2019) found that informative content generated fewer shares compared to emotional content, which could be attributed to the fact, that informative content can be perceived as dry (pp. 1, 11).

Entertainment is another central aspect of why users consume specific social media content and includes different sub-categories, according to Muntinga et al (2011, p. 28). In addition to informativeness and irritation (a demotivator) it tends to be one of the most important motivational factors for consuming content, as it addresses users' needs for escapism, hedonistic motives, and emotional stimulation (Ashley & Tuten, 2015, p. 19). It includes the motivations enjoyment, relaxation, and pastime (Ashley & Tuten, 2015, p. 28). Whether it is for the mere pleasure of consuming brand-related content, catching a break from everyday life, or killing time without a specific goal, entertaining content not only brings short-term fulfillment, but also addresses basic psychological needs for relaxation. Entertaining content can be defined as the combination of brand messaging and entertainment value (Zhang et al., 2010, p. 53). Hudson and Hudson (2006) even view this type of content as an extension of product placements in their traditional form (p. 489), because it integrates brand messages into a light-hearted, playful context. Consumers who look for entertaining content are often motivated by a need for relaxation, fun and social interaction, for example through playing or exchanging messages with others (Dholakia et al., 2004, p. 244). Wiese and Akareem (2020) found that entertaining and informative content support a positive attitude toward brand messages on social media (p. 430). Moreover, entertaining content has been found to promote engagement with brands by users (de Vries et al., 2012, p. 85), even more if it incorporates playful or interactive aspects. This gamified content can even positively influence brand equity and brand perception (Alanadoly & Salem, 2024, p. 395). A content analysis of branded entertainment on Facebook by Zhang et al. (2010) found that 70% of the analyzed material included branded entertainment, which further demonstrates how traditional play themes are incorporated in brand communication on social media (p. 58).

The third relevant content type is promotional content, which, in the context of marketing, aims at inspiring favorable actions for the product or service of a brand (Tellis et al., 2019, p. 4). According to existing literature, people interact with promotional content in hopes of receiving rewards. These can be for example in their work life, their personal life, or an economic benefit (Muntinga et al., 2011, p. 21). Content on social media that provides a reward or payment may take the form of financial inducements, giveaways, prize draws, or cash compensations. (Füller, 2006, p. 641). Ashley and Tuten (2015) found that in order to gain more reliable followers through promotional content, top brands organize contests, rather than handing out simple discount codes or coupons (p. 24).

The effect of content types on consumers varies depending on the circumstances of the study. While Lee et al. (2014) showed that sole informative content tends to attain lower user engagement than persuasive content, combining both types increases engagement (p. 1), a study by Cho (2021) found that posts on Instagram with an informative focus and a lower value of entertainment significantly increased trust, which positively affected user engagement (p. 54). Furthermore, personal taste and preference play a big role in content perception, though it can be generally said that funny, entertaining, newsworthy, and/or utilitarian content is appealing to a wide majority, which in turn promises higher engagement (Sydral & Briggs, 2018, p. 18).

Incorporating a mix of various content types offers various advantages. It offers brands the opportunity to satisfy different consumer needs, attract and address various types of users, and ensure a diverse range of content. Through all these aspects, interactions between brands and users are stimulated, which highlights the importance of understanding how each type of content resonates with the audience. This provides an essential foundation for understanding how users engage with brand content on social media.

Consumer Engagement on Social Media

Understanding how different formats and types of content elicit distinct reactions from users, and how they engage with this content, is a central aspect of marketing research. The word "engagement" has been used in research across various academic fields for several decades. However, its application within marketing, connected with other terms, such as "customer engagement", has only emerged in literature after the year 2005 (Brodie et al. 2011, p. 252). When researching a definition of the concept of engagement, various definitions can be found (Dessart et al., 2016, p. 402). Despite the conceptual diversity, it is imperative to acknowledge the importance of consumer engagement in shaping and strengthening brand development. This type of engagement can be described as a "consumer's positively brand-related cognitive, emotional and behavioural activity during, or related to, focal consumer/brand interactions" (Hollebeek, 2014, p. 149). This definition emphasizes the complexity and multidimensionality of engagement, while the behavioral aspects appear most frequently employed in scientific research, given their relative ease of measurement (Trunfio & Rossi, 2021, p. 267). Definitions of engagement within marketing can be split into engagement with a psychological focus or behavioral one, and some definitions include both aspects, according to Maslowska et al. (2016, p. 471). Behavioral engagement refers to customer actions toward a company that are driven by motivational factors and exceed purchase transactions (Van Doorn et al., 2010, p. 254; Verhoef et al., 2010, p. 247). Higgins and Scholer (2009) define psychological engagement as being strongly involved or immersed in a specific item or activity (p. 102). Differentiating between the two types is crucial because it determines how engagement should be operationalized and measured in each individual study. Engagement can be considered a cyclical process, which simultaneously affects and is affected by participation, trust and commitment (Brodie et al., 2011, p. 258), while the stated process may vary for new and established customers (Bowden, 2009, p. 65). This can be explained by the fact that affective commitment develops over time (Bowden, 2009, p. 65). Therefore, engagement needs to be viewed as a dynamic concept, instead of a static outcome.

Features that influence engagement can be divided into three categories: factors related to the creator (e.g. age, sex, brand vs. individual), the post context (e.g. time, location) and specific features of the content, depending on whether it is written, visual or audio content (Jaakonmäki et al., 2017, p. 1152). Through this categorization, it is possible to gain further insight into why levels of engagement vary between posts and platforms through a structured context.

Engaging customers through the content that is posted is the main goal of a brands presence on social media, as it allows brands to establish a more interactive relationship with users. Additionally, user engagement strongly affects people's view and attitude toward brands which is important as people are more likely to buy a product, if the public opinion of that product is high (Agarwal et al., 2022, pp. 1,5). Thus, engagement is not only an outcome of marketing activities, but also a driver of behavior of consumers. Nowadays, engagement is considered as a key metric in order to judge whether social media campaigns are considered successful (Vohra & Bhardwaj, 2019, p. 89). Drawing from Wahid et al. (2023), who based their definition on Dolan et al. (2016, p. 265), social media engagement is defined as "behaviors go beyond transactions, and may be specifically defined as a customer's behavioral manifestations that have a social media focus [adapted], beyond purchase, resulting from motivational drivers" (p. 110). This coincides with a definition by Sydral and Briggs (2018), who state that social media engagement is not only measured through likes, comments and other metrics, but is rather a psychological state, that can exist independently from these interactions (p. 4). These definitions reflect the dual nature of engagement as measurable and experiential.

Different factors such as the content, the size of the account, posting time, etc. can influence user engagement (Agarwal et al., 2022, p. 2). Moreover, text-specific-aspects can have significant impact as well. Providing content that is simple and can be understood easily increases the probability of positive reactions and engagement from users (Davis et al., 2019, p. 151). While Instagram is a social media platform with a visual focus, the accompanying caption can still have a strong impact on users reaction to a post (Yu et al., 2025, p. 853). Additionally, they make communication easier and deliver important information (Hooker & Cooper, 2022, p. 6), which highlights how important a multimodal content design can be in engagement processes.

On Instagram users can show measurable engagement in different ways. According to Dolan et al., engaging passively could be saving a post or just viewing it, engaging moderately active would be liking or sharing it and highly active engagement would be to leave a comment on a post (2019, pp. 2216-2217). In comparison to this, Schivinski et al (2016) established a scale to aid in measuring consumer engagement on social media content of brands. For this purpose, they based their construct on three dimensions of engagement established by Muntinga et al (2011) in an earlier framework of "Consumer's Online Brand-Related Activities". In line with their belief of the need of differentiating between levels of engagement from the perspective of consumer they included the dimensions consumption, contribution and creation (pp. 65-66). Both models work with three dimensions but differently categorize actions (Table 3). This deviation is relevant because of how it influences the interpretation of level of engagement behavior and will be addressed in a later chapter of this paper.

Table 3

Comparison of levels of engagement between two conceptual models.

Levels of engagement according to Schivinski et al. (2016, p. 66)	Examples for engagement according to Schivinski et al. (2016)	Levels of engagement according to Dolan et al. (2019, p. 2217)	Examples for engagement according to Dolan et al. (2019)
Consumption	Viewing a brand-related post on social media.	Consuming	Viewing or saving a brand-related post on social media.
Contribution	Liking or commenting on a brand-related post.	Contributing	Liking or sharing a brand-related post.
Creation	Posting a picture on your personal account with said product.	Creating	Commenting on a brand-related this post.

Note. This table compares the three different levels of engagement defined by Schivinski et al (2016, p. 66) and Dolan et al (2019, p. 2217). Both frameworks show how the authors classify user engagement on social media.

While comments are always visible to the public, likes can be hidden by the creator. As they are rarely hidden on brand accounts, a high number of likes and comments can motivate more users to engage with the post, as humans often tend to follow the action of a crowd (Wahid et al., 2023, p. 110). Besides the quantity of comments, their tone and valence can affect user behavior too. Prior research by Dutceac Segesten et al. (2020) showed how being exposed to disagreeing comments draws the visual attention of users' to the comment section, and simultaneously decreases their willingness to share a post (p. 1115).

Engagement is shaped by several factors connected to the individual, as well both structural characteristics of a platform, as well as qualities of the content itself (Jaakonmäki et al., 2017, p. 1152). Digital environments are constantly evolving, especially now with the increasing implementation of AI in this context. Gaining a better understanding of how users respond to different types of brand communications becomes increasingly important in order to identify successful marketing activities.

GenAI in the Context of Social Media Marketing

The growing integration of AI is changing how content is produced, distributed, and consumed across various platforms. GenAI can greatly support both users and providers of social media platforms. Benefits like automatically identifying harmful content on these apps or improving the workflow of content creation make its incorporation attractive (Pan et al., 2024, p. 1). Even though research regarding the implementation of GenAI tools such as ChatGPT is in its early stages, it is evident that these programs are increasingly integrated into digital marketing processes, especially in areas like content creation or campaign development (Gołąb-Andrzejak, 2025, p. 1130).

Content produced by AI, which can come in the shape of text, photos, or videos, is defined as "AI generated content" (Du et al., 2023, p. 122). GenAI-tools have completely changed the process of content creation and have thus become essential for fulfilling marketing goals. They are able to streamline the necessary steps for content creation, regardless of whether it is social media posts, articles, or some other form of content (Lanfranchi et al., 2025, p. 14). ACC is widely appreciated due to its ease of application, its accessibility to a broad range of users, and its ability to rapidly produce content that is perceived as high in quality (Mohammadi & Jafari, 2024, p. 435). Due to these benefits of AI, the number of companies and marketers expected to use AI for this purpose is increasing (Mohammadi & Jafari, 2024, p. 435). Up until recent years, the person in charge of social media or content production at companies led photo and video creation, wrote accompanying texts, or selected assets for output (Du et al., 2023, p. 122). This has already drastically changed and likely will continue to do so in the future. This change in content generation is not only affecting companies, but also consumers and their reactions. Companies reported significantly increased leads and conversion rates after incorporating GenAI-generated content (Grewal, 2025, p. 1). Additionally, GenAI tools provide strong support in communicating with existing customers and increasing engagement (Saxena & Khanna, 2013, p. 23; Filo et al., 2015, pp. 166, 173) and have simultaneously influenced how brands communicate with consumers (Oklander et al., 2024, p. 2).

GenAI can be applied in different forms. According to a survey conducted by the Boston Consulting Group's in April 2023, the three most common applications in marketing were personalization, insight generation, and creating content (Kshetri et al., 2024, p. 2). Especially personalization appears to be one of the standout applications in marketing, as intense data analysis enables customization of the content so that it meets users' needs (Lanfranchi et al., 2025, p. 14). When incorporating GenAI-tools in content creation, it can reduce production time to a fraction of the time it would take a human to do the same, which allows businesses to reduce time and cost for content creation and focus more on other areas (Islam et al., 2024, p. 6; Lanfranchi et al., 2025, p. 13). McKinsey & Company (2023), a management consulting firm, even estimated that GenAI-tools could improve productivity to a level, which could in turn save between 5% to 15% of marketing spendings. Additionally, they also estimated that GenAI and other technologies, already available in 2023, could potentially provide automated processes for work tasks that take up 60% to 70% of working time, which further highlights how much time can be saved by incorporating GenAI in daily processes. A survey by Salesforce (2023) estimated that about 5 hours per work week could be saved by using GenAI, which would add up to about a month's worth of working time per year.

Considering all these benefits, it does not come as a surprise that many businesses are incorporating GenAI into daily work life. In a survey conducted by Davenport et al. in 2023, more than three quarters of 300 questioned chief data officers believed that GenAI would fundamentally change their work environments (p. 8). Additionally, more than half of them planned to increase investments in AI (p. 9), which again emphasizes the relevance and growth agenda of these tools. But it is not only employees of a company who incorporate GenAI-tools. Big companies such as Meta have started providing different GenAI-tools to their customers (Kshetri et al., 2024, p. 2). Whether that is automatic text modification, automated creation of new pictures for ads, or the cropping for pictures depending on what seems to help achieve the goals that were set.

Furthermore, models like ChatGPT offer the opportunity to easily adapt specific content to different platforms. This increases scalability, makes content adaptable for various platforms, and allows seamless content creation and delivery (Lanfranchi et al., 2025, p. 13). This is particularly valuable, since it is recommended to tailor content to each platform, as the various algorithms rate content differently (Shahbaznezhad et al., 2021, p. 61). Furthermore, GenAI can help in identifying the optimized distribution timing to complement the circumstances of the platform algorithm (Lanfranchi et al., 2025, p. 14). Another stage of the marketing process GenAI can be used for is planning. While the support in actively creating content is highly relevant, GenAI can also serve as a highly capable assistant that has the capacity to develop or improve editorial plans easily (Lanfranchi et al., 2025, p. 13).

While AI has numerous advantages, it also has its flaws. These range from making up information (Pavlik, 2023, p. 92) and being inaccurate to having a tendency toward monotony and lack of originality (Houde et al., 2020, p. 3). Another significant challenge when incorporating GenAI in content creation, is maintaining authenticity (Capterra, 2025). Marketing experts questioned by Lanfranchi et al (2025) agreed that specifically for marketing content with a high emotional impact, GenAI does not show a sufficient level of empathy and does not find an appropriate tone of voice (p. 15). When asked in more detail, experts explained that due to these limitations of GenAI, the human mind is irreplaceable for this task (p. 15). They went on to say that what is needed to create engaging and creative content, traits like human intuition, empathy, or even critical thinking, cannot be provided by AI (p. 15). This shows the relevance of collaboration between AI and humans, even more when creating emotionally stimulating content. Hence, content created with GenAI should always be reviewed.

With the rise of AI-technologies, not only the automation of content is changing, but also how humans and machines „work together" to produce this content. Even before reviewing the output, marketers need to develop prompt engineering skills in order to use GenAI effectively (Lanfranchi et al., 2025, p. 16). This human augmentation, the targeted revision of output from GenAI-tools by humans (Grewal et al., 2024, p. 710), is simultaneously gaining relevance and should always be considered to minimize the risk of putting out inappropriate content (Tamkin et al., 2021, p. 7). The collaboration between GenAI and humans can be especially beneficial during the creative process, though concerns about the use of GenAI decreasing linguistic and writing skills are also prevalent (Lanfranchi et al., 2025, p. 15). In order to determine the level of human augmentation of output, cost and risks need to be assessed (Grewal et al., 2024, p. 713).

In their four-quadrant-framework for content creation, Grewal et al. (2024) discuss different extents of this interference by humans (p. 714). In this framework, tasks in Q2 require a generalized input but a high level of involvement by a human for the output, which delays its delivery (p. 715). Grewal et al. (2024) mention the creation of a social media post by ChatGPT as an example of this quadrant. Benefits of this approach are obvious, such as the minimization of hallucinations and mistakes (p. 715). Additionally, since the published content is created by AI but validated by a human, it could increase trust by recipients, which is necessary in regard to perception of authenticity and brand loyalty, according to the commitment-trust theory (Morgan & Hunt, 1994).

Although companies have reported positive effects of implementing GenAI, these insights are mostly based on the practitioner's perspective. Nonetheless, the uncertainty of how user engagement is affected by ACC remains highly relevant, as research about this topic is limited (Mohammadi & Jafari, 2024, p. 435). In sum, the rise of GenAI is fundamentally changing the field of social media marketing by transforming content creation, workflows, and interaction with users. Simultaneously, the implementation raises critical questions about authenticity, trust, and the need for humans to oversee the processes. This evolution affects marketers, but also shapes how users view, interact with, and judge content. These dynamics require a deeper understanding of the underlying mechanisms, therefore, the following chapter will introduce three theoretical frameworks, which offer a structured view of user motivations, dynamics between brands and consumers, and reactions to digital content.

Theoretical Foundations

It is imperative to call on relevant theoretical frameworks to better explain how individuals select, interpret and respond to digital content, which is a focus point in contemporary marketing research.

Uses and Gratifications Theory

The uses and gratifications theory, introduced by Katz et al. (1973a), states that humans seek content, that satisfies personal needs in terms of character and social context (p. 510). Therefore, it is commonly used to identify users' motivations for using different types of media and focuses on why people use media, instead of how it affects them (Qin, 2020, p. 338).

McQuail (1983) suggested one of the most widely accepted categorizations of the uses and gratifications approach and stated three different motivational factors for consumption of media content: amusement, self-definition and informational needs (McQuail, 1983; Qin, 2020, p. 339). Whiting and Williams (2013) consider the informational need as gathering new information or educating oneself (p. 364), while amusement means looking to be entertained through social media use (Qin, 2020, p. 339). Self-identity as a motivational factor includes all intentions connected to oneself, such as sharing personal opinions, or receiving attention from others (Muntinga et al., 2011, p. 20). Ko et al. (2005) added convenience as a fourth motivator, meaning that social media provides users with what they crave without requiring a lot of effort (p. 60). Similarly, Rohm et al. (2013) stated that seeking entertainment, engaging with brands, gathering the latest information about the brand and their products and making use of incentives or promotional offers are main motivators for consumers to interact with brands (p. 295). Katz et al. (1973b) also emphasize the relationship between characteristics of media and which psychological as well as social roles they fulfill (p.165). In this context, Swanson (1987) highlights the relevance of the topic of the transported message (p. 245). According to Schweiger (2007), users of media are active and have a goal, so their activity serves a purpose: achieving a specific effect (p. 61). Looking for information about a brand to make a well-informed pre-purchase decision falls into the category of functional motives (Hollebeek & Macky, 2019, p. 32). Choosing media in hopes of being entertained or feeling relaxed is considered a hedonic motive, while the authenticity motive refers to the user's need of connection with others (Hollebeek & Macky, 2019, p. 32). Hollebeek and Macky (2019) state that the authenticity of DCM encompasses users desire for continuity, meaning that content is perceived as true to the brand, integrity, referring to the perception that the company is motivated by a sense of responsibility and symbolism, which reflects the extent to which consumers feel supported by a brand in being true to themselves (p. 33; Morhart et al. 2015, p. 202).

Building on these traditional U&G theory categories, more recent work extends the framework to online contexts, specifically DCM. Hollebeek and Macky (2019) identify three precursors of DCM, a functional, hedonic or authenticity motivation (p. 31). Contrary to this, Schenk (2007) states that this assumption does not apply to every behavior of media use (p. 704). When it comes to habitualized or ritualized consumption, which is often part of daily behavior, choosing media is not carried out intentionally but more out of habit (Schenk, 2007, S. 704). In these cases, motives for unintentional or passive media consumption include wasting time, distraction, or relaxation (Schenk, 2007, S. 705). Steiner and Xu (2020) propose that attention should be considered on a spectrum that consists of different levels of engagement, which depend on the motivation behind media use (p. 82). This activity tends to be higher in the field of digital media (Ruggiero, 2000, p. 19), which might be explained by the more interactive character of new media (Sundar & Limperos, 2013, p. 505).

In the field of social media research, the uses and gratifications approach has been employed widely, since the theory has its origin in communication science, which supports its application in this context (Whiting and Williams, 2013, p. 363). Until around 1950, early communication science studied the effect of media on opinions and actions, while assuming that audiences were spreading brand messages passively, without thinking critically (Schenk, 2007, p. 7). The uses and gratifications approach, in contrast, focuses on active users who consciously choose certain media to fulfill their psychological or social needs (Quan-Haase & Young, 2014, pp. 348-349). Following a brand on social media can be interpreted as an active decision to interact with contents published by brands and can be explained by the motivation of consumers to strengthen and express their identity (Islam, 2024, p. 3; Muntinga et al., 2011, p. 29).

Whiting and Williams (2013) researched different reasons why people use social media. The most common were the longing for interaction with others, to gather information, to pass time and be entertained are the most common reasons (p. 368). Smock et al. (2011) explain how different features within a social media platform can be purposefully used in order to fulfill different goals (p.2322). This feature-specific approach can gain relevance, because while users browse on Instagram, they interact with content that meets their current needs, such as being entertained or finding relevant information. In order to identify the different types of customer experiences and the motivators behind their engagement in online brand communities, U&G approaches have been applied broadly (Fujita et al., 2018, p. 66). This shows how well-established this theory is for understanding brand-related social media use.

Katz et al. (1973a) assumed that users are aware of their motives for media use (p. 510). Moreover, Albisser (2022) states that humans have different needs, though some of these needs can be satisfied through media use (p. 66). The different possibilities to satisfy needs are called functional alternatives (Lichtenstein & Rosenfeld, 1983, S. 100). This concept explains that similar needs can be satisfied through different activities, for example wanting to be entertained can be done by reading a book or by going on a walk (Lichtenstein & Rosenfeld, 1983, S. 100). Therefore, media compete with other means of gratification and different media are better or worse suited to satisfy these needs (Lichtenstein & Rosenfeld, 1983, S. 100). Social media platforms that satisfy different primary needs create different reception contexts which in turn affect how brand content is perceived and addressed.

It can be distinguished between gratifications sought and gratifications obtained (Dobos, 1992, p. 30). Gratifications sought can be defined as needs, expectations or motivations and are formed by characteristics of a person or the social surroundings (Dobos, 1992, p. 30). Gratifications obtained or need gratification describe the actual fulfillment of those needs through media that is consumed (Dobos, 1992, p. 30). If motives of sought gratification are known, then brands can try to satisfy this need with their communication and content (Albisser, 2022, p. 68).

Since the satisfaction of these desires can potentially be factors that influence user engagement, there could be a notable difference in how ACC and HCC fulfill these needs. This difference could in turn be visible in user engagement metrics. If ACC is perceived as less authentic or emotionally resonant, it could lead to a decreased sense of interpersonal closeness or „confirmation" of identity. These differences might be less pronounced for informative content, where factual accuracy is a priority. These insights show how the U&G

theory provides a theoretical framework for the motivators behind choosing content and how brand communication, including emerging forms of AI-generated content, is evaluated by consumers.

Commitment-Trust Theory

The commitment-trust theory, proposed by Morgan and Hunt (1994), provides a relational perspective on how lasting relationships between brands and individuals are formed and maintained, which is applicable to the digital context. It states that trust and commitment are central aspects of establishing long-standing relationships, especially in business-to-business and business-to-consumer contexts (p. 20). With reference to this theory, trust refers to a consumer believing in the reliability and integrity of a partner and commitment concerns the willingness of a partner to maintain a relationship indefinitely (p. 23). Later, Rousseau et al. (1998) defined trust as being willing to show vulnerability, because of the expectation that the other party is reliable and has good intentions (p. 395). Trust includes aspects from various disciplines, such as, psychology, marketing and even decision science (Mukherjee & Nath, 2007, p. 1177). Mukherjee and Nath (2007) identified five precursors of trust: (a) shared values; (b) communication, (c) opportunistic behavior; (d) privacy; and (e) security (p. 1178).

Particularly relevant in the context of social media is the aspect of communication. Mukherjee and Nath (2007) state "openness", "quality of information" and "quality of response" as the most important factors of communication (p. 1178). How the quality of communicated information is perceived depends on how authentic, relevant and complete it is (Mukherjee & Nath, 2007, p. 1179). While the online context and the lack of social presence thereof are believed to hinder the creation of consumer trust (Gefen & Straub, 2003, p. 7), a consistent and high-quality interaction with brands on social media can compensate for this barrier (Huyen et al., 2024, p. 58). Gefen and Straub (2003) further stated that for trust to develop in online communication, interaction with a human, or at least the belief of characteristics of social presence portrayed by a system, is crucial (p. 7).

Trust can take on different forms. In the exploration stage it can be based on reputation, while during the stage of commitment it can be based on past experiences (Flavian et al., 2006, p. 3). Brand commitment refers to "the extent to which stakeholders are willing to work for the brand and its success" (Merz et al., 2018, p. 82) and is crucial, because strongly committed customers stay loyal to the brand, without considering other ones within a specific product class (Huyen et al., 2024, p. 59). For the purpose of their study which was conducted in a digital environment, Kang et al. (2014) explained brand commitment as the decision by users to maintain a relationship with the company though being active in online communities (p. 148). Relationship marketing, as defined by Morgan and Hunt (1994), includes all activities that aim to cultivate, build and maintain successful exchanges in relationships (p. 22). This theory provides a foundational framework for how relationships are impacted by trust and relationship commitment in an online context (Rashidi-Sabet & Bolton, 2024, p. 1300). Rashidi-Sabet & Bolton (2025) claimed that establishing commitment and trust between two parties are two essential factors for successful, long-lasting relationships (p. 1301).

Morgan and Hunt (1994) further identified ten discrete forms of relationship marketing, which can be categorized in into four groups of supplier, lateral, buyer, and internal partnerships (Morgan & Hunt, 1994, p. 21). In accordance with this, Rashidi-Sabet and Bolton (2024) stated that social media can be viewed through three different perspectives: consumers, firms, and public policy (p. 1304). The ten discrete forms of relationship marketing can be divided in consumer-to-consumer, consumer-to-firm, firm-to-consumer, firm-to- firm, and public policy interactions (Rashidi-Sabet & Bolton, 2024, p.1304) and they all influence commitment and trust differently. The form that is most relevant to this study is the firm-to-consumer relationship, which stands for the interaction between brands and users on social media.

Another central element of the commitment-trust theory (Morgan & Hunt, 1994) are shared values between two parties, as they are the only precursor that directly influences commitment and trust (p. 25). Shared values describe the "extent to which partners have beliefs in common about what behaviors, goals, and policies are important or unimportant, appropriate or inappropriate, and right or wrong." (Morgan & Hunt, 1994, p.25).

The theory was established during a time when the internet was just at its beginning, therefore, in their theory, Morgan and Hunt (1994) assumed the physical presence of all parties involved, while researching how the two factors are connected (Allison & Blair, 2025, p. 2). Nonetheless, it is obvious that Morgan and Hunt (1994) determined universal dynamics of relationships, that are able to withstand technological changes (Allison & Blair, 2025, p. 2). Organizational commitment literature tends to differentiate between two types of commitment, one of which is particularly relevant to this paper: the commitments shown by people who share, identify and internalize values of the organization (Morgan & Hunt, 1994, p. 25).

In the context of digital brand communication, this aspect gains relevance. Social media is consistently gaining relevance as an important pillar in brand communication, as

companies rely on this marketing channel to connect directly with customers (Hudson et al., 2016, p. 27). With a strong appearance, active firms have the power to influence users purchase behavior and customers perceptions of a brand (Gensler et al., 2013, p. 245) and can establish a strong relationship with customers and influence their future spendings through enhancing the frequency of customer visits and their profitability (Rishika et al., 2013, p. 125). For brands, being active on social media is highly relevant in order to establish brand trust of consumers (Ebrahim, 2020, p. 301), which, in consequence, is needed for long-term commitment (Wong
, 2023, p. 87). User engagement plays a relevant part in establishing a relationship that is based on commitment and trust, which satisfies both parties and creates an emotional bond between an individual and a brand (Pansari & Kumar, 2017, p. 308). There is the possibility of increasing commitment and trust of brands and customer through strategi activity on social media, which can happen through consistently promoting interactive engagement from both sides (Rashidi-Sabet & Bolton, 2024, p. 1307; Pansari & Kumar, 2017, p. 295). Interacting with a brand on social media makes it more trustworthy in a cognitive, as well as an affective (emotional) sense (Huyen et al., 2024, p. 58). Cognitive trust refers to a conscious calculation of perks in the form of a rational decision, while the perceived sense of security and comfort while relying on a brand is considered as emotional trust (Choi & Lee, 2017, p. 552) However, Cho (2021) found that cognitive trust has more influence on user engagement than emotional trust (p. 51).

Research has shown that there are big risks connected to social media platforms that can significantly impact the marketing relationship (Rashidi-Sabet & Bolton, 2024, p. 1304). These risks include privacy concerns, echo chambers created through algorithms, negative consequences from excessive social media use that in the end shed negative light on companies on social media (Rashidi-Sabet & Bolton, 2024, p. 1304). All these factors can directly or indirectly damage trust and credibility of brands that operate online.

These constructs, trust and commitment, are especially relevant, when replacing material produced by a human with AI-generated content in social media marketing. If a change in content is detected by users, it may reduce their trust in the brand and their commitment, potentially resulting in lower willingness to engage. Therefore, this theory provides an essential base for understanding how authenticity and reliability are interpreted in digital spaces.

Brand Authenticity

The concept of brand authenticity further deepens the understanding of how consumers evaluate brands. In digital marketing, this is particularly relevant, as authenticity needs to be conveyed without physical presence. Authenticity is crucial for consumers and is one of the foundations for contemporary marketing (Brown et al., 2003, p. 21). Stern (1994) was the first one who brought the aspect of authenticity into the realm of marketing (Södergren, 2021, p. 645) and since then the importance of authenticity is clear and apparent when taking a closer look at modern advertisements and marketing efforts in general (Södergren, 2021, p. 646). Authenticity for brands is crucial and also difficult to establish, as marketing tends to be seen as naturally inauthentic (Deibert, 2017), which leads to some tension between commercial motives and the aim of genuine brand communication.

For a long time, it was difficult to establish a shared definition of authenticity that was commonly accepted, as researchers often just defined authenticity according to the context or subfield they were investigating (Nunes et al., 2021, p. 1). In the context of consumption, authenticity can be defined as "a holistic consumer assessment determined by six component judgments (accuracy, connectedness, integrity, legitimacy, originality, and proficiency) whereby the role of each component can change according to the consumption context"(Nunes et al., 2021, p. 2). Two components are particularly relevant to authenticity in the context of social media and AI: accuracy and connectedness (Nunes et al., 2021, p. 3). Accuracy can be defined as "The extent to which a provider is perceived as transparent in how it represents itself and its products and/or services and, thus, reliable in terms of what it conveys to customers"(Nunes et al., 2021, p. 3). Connectedness is "the extent to which a customer feels engaged, familiar with, and sometimes even transformed by a source and/or its offering"(Nunes et al., 2021, p. 3).

With the rise of social media platforms, the dynamics between consumers and brands have drastically changed. Today, users have the possibility to share their brand-related opinions and experiences within seconds with people worldwide and at the same time, users can inform themselves easily, due to the availability of reviews and information online (Campagna et. al., 2023, p. 129). As a result of this shift, brand authenticity has gained importance (Schmidt & Iyer, 2015, p. 433).

In short, being authentic is "being genuine, open and honest" (Campagna et al., 2023, p. 137). Campagna et al. further defined three components of authenticity: consciousness, longevity and self-empowerment (pp. 139-140). This signifies that companies need to be reflective and aware of societal changes, remain true to their values while being adaptable and establish emotional connections, as well as inspire self-empowerment. For brands, being perceived as authentic is crucial in order to build up a strong identity and connection to followers (Campagna et al., 2023, p. 129). For brands, being perceived as authentic is crucial, as it increases trust and brand equity (Portal et al., 2019, p. 725). Additional results of brand authenticity are brand trust, brand loyalty, perceived quality and cultural iconicity (Södergren, 2021, p. 655).

Brand authenticity can be described as "the extent to which consumers perceive a brand to be faithful and true toward itself and its consumers, and to support consumers being true to themselves" (Morhart et al., 2015, p. 202). However, the idea of brand authenticity needs to be viewed as ambiguous and multilayered, since it comprises numerous dimensions that need to be interpreted differently, depending on the context (Akbar & Wymer, 2017, p. 18). Other factors tied to it include uniqueness, sincerity, and genuineness, all of which contribute to consumers' perception of authenticity (Napoli et al., 2014, pp. 1090-1091).

To build up authenticity, brands need to show admiration and passion for their craft, as well as maintain consistency in their processes (Brüns & Meißner, 2024, p. 4). If these principles are not followed it can lead to being perceived as inauthentic (Silver et al., 2021, p. 76). Factors like stylistic consistency and congruence need to be considered when aiming to appear authentic (Schallehn et al., 2014, p. 192). When communication emphasizes heritage and stays true to its origin and its core values, chances are higher that it are seen as authentic (Södergren, 2021, p. 653). As consumers tend to dislike changes such as new logos by brands (Brown et al., 2003, p. 24) a tendency of resistance against change in brand expressions is evident. Authenticity is often tied to consistency, which is why any modification, whether that would be a new logo or a different communication style, can be perceived as a loss of genuineness.

With the passing of time, values like honesty, responsibility and transparency have become relevant in the context of authenticity (Södergren, 2021, p. 646). Authenticity that is shown through companies really believing in their offer, improves consumers view on the economic value (Hernandez-Fernandez & Lewis, 2019, p. 222). In addition, the ADO (Antecedent, Decision, and Outcome) framework by Paul and Benito (2018) can serve policymakers or practitioners as a support in positioning and framing a brand as authentic (Södergren, 2021, p. 646).

Theoretically, brand authenticity can be understood in two forms: the iconic approach and the indexical approach (Grayson and Martinec, 2004, p. 296). The iconic approach assumes that people project their own meanings onto brands for self-authentication (Grayson and

Martinec, 2004, p. 298). The indexical approach on the other hand suggests that consumers focus on historical meanings and attach those to brands (Grayson and Martinec, 2004, p. 297). Grayson and Martinec (2004) further argue, that there is a slight difference between evaluating whether one perceives themselves as authentic and judging someone else's authenticity (p. 297), which highlights the subjective nature of authenticity perception.

Brand authenticity also plays an important role for identity construction, as it is highly relevant in regard to consumers identifying themselves with brands, since they can serve as a symbolic resource that helps consumers express their own values and sense of self (Morhart et al., 2015, p. 202). Authenticity of brands is often expressed and perceived through social media marketing (SMM). However, there has long been a lack of research regarding brand authenticity in the context of SMM, especially the impact of dimensions of social media marketing on perceived brand authenticity (Hasan et al., 2023, p. 871). Moreover, research has neglected the underlying mechanism between activities on social media and brand authenticity (Hasan et al., 2023, p. 871). In order for brands to establish and convey brand authenticity through SMM, a clear refined message is crucial (Dwivedi and McDonald, 2018, p. 1388). In the end, authenticity of a brand is judged by the consumer (Dwivedi and McDonald, 2018, p. 1391). Among the dimensions of brand authenticity stated by Hasan et al. (2023, p. 873), they listed continuity, reliability and credibility - all of which are incredibly relevant to the social media appearance of brands. From showing stability and consistency, to trustfulness and transparency, all these aspects are essential to be perceived as authentic by social media users. Additionally, entertaining content has been shown to positively influence brand authenticity, as well as social media marketing outcomes in general (Hasan et al., 2023, pp. 881, 883), which highlights that authenticity does not exclude enjoyment or creativity, but instead can be increased through engaging and meaningful interactions.

While all theories stated above provide insight into the motivation of how media is chosen and relationships between brands and users are established, they neglect the possible change and effect of ACC, as they were developed during a time, when content for media was mostly created by humans. Consequently, these theories are based on an initial situation, where a consumer is viewing authentic human material. Once consumers realize that they are not interacting with HCC anymore, a new layer gains relevance - one that has the potential to disrupt perceived authenticity and trust, even when the content quality remains high. Given that trust and authenticity are central pillars of a successful brand-consumer relationship, a sudden change in the perceived sincerity of the output could potentially lead to immediate negative consequences, irrespective of the actual quality. Nonetheless, the theoretical foundations remain valuable as they provide insights into the underlying mechanism of users motives for media use, the relationships with brands and factors that affect the relationship strongly.

In combination these three theoretical frameworks provide complementary insight into how users behave in digital environments. While the U&G theory provides insight into why media is chosen, the commitment-trust theory emphasizes important relational factors, necessary for successful brand-consumer relationships. Additionally, authenticity highlights aspects like continuity that influence users' judgment or brand communication. Together they shed light on motivational, relational and perceptual mechanisms through which user behavior in the context of social media can be explained. This reiterates the importance of analyzing previous research on consumer reactions to ACC and identifying gaps in the collective understanding of its effects on authenticity or trust when implementing AI tools in content creation.

Previous Research and Research Gap

After outlining the relevant theoretical frameworks in this context, it is important to take a closer look at previous research that examines how ACC impacts recipients under different circumstances. As GenAI has not been available to the broad mass for a very long time, it is a comparatively new field for research in the context of marketing. Nevertheless, several experimental studies have investigated how content created using GenAI affects aspects such as consumer perception, brand authenticity or engagement – often compared to HCC.

Earlier research, such as Wu and Jing Wen (2021), studied how consumers respond to AI-generated advertisements, before the rise of GenAI-models. More specifically, Wu and Jing Wen (2021) examined which factors influenced consumers' perception of advertisements created using AI (p. 133). Their findings showed that the machine heuristic, a positive bias toward output created by machines, and perceived eeriness influenced perception (p. 140). Furthermore, ads that were seen as objective and competent were appreciated more by consumers, whereas ones that caused feelings of eeriness or discomfort were appreciated less (p. 140). This study emphasizes how trust in technology and emotional unease can influence consumers' evaluation of marketing content that was created using AI. Although the findings of this study are conceptually relevant, its focus on psychological mechanisms rather than GenAI or social media communication falls outside the scope of the studies summarized in Table 4.

A study by Jakesch et al. (2023) investigated whether people could accurately identify AI-generated language in self-presentations in different online contexts (p. 1). In six different experiments, 4,600 participants did not correctly identify AI-generated text and human-written text (p. 1). Further analysis showed that participants relied on flawed heuristics, which were often misleading (p. 1). The findings of this study suggest that human intuition can be unreliable when one needs to evaluate whether content is produced by another human or by AI, which in turn has important implications for how consumers might perceive AI-generated content in general. Nonetheless, this study was based on judging texts which were presented to participants without a social context.

Though the literature in this field is still limited, a few researchers commenced to investigate the effects of the incorporation of AI into different areas. Relevant findings from recent studies that specifically address the use of GenAI in marketing and communication contexts have therefore been summarized and presented in Table 4.

Table 4

Previous empirical studies on consumer and user responses to ACC in marketing and communication contexts.

Source	Focus	Summary	Relevant results	Method
Gu et al. (2024)	Investigated whether advertisements created using GenAI are accepted by consumers, judged through visual ad features and perceived through psychological perception (p. 2218).	Participants were asked to remember an AI-generated ad and judge it. Verisimilitude, vitality, imagination, synthesis, perceived eeriness, perceived intelligence, and willingness to accept were judged through answering subjective questions (p. 2226). Valid responses were collected from 1147 participants in China (p. 2226)	Realistic and imaginative AI ads are more accepted by consumers. Synthetic or artificial-feeling ads cause discomfort. Perceived intelligence increases acceptance (p. 2218).	Questionnaire survey (p. 2226)
Ratta et al. (2024)	Explores the difference between ACC and HCC in advertisements and their effect on	The possibilities and accuracy of AI is discussed in the context of advertising, with a focus on emotions	ACC was more effective in generating user engagement and purchase behavior	Semi-structured interviews with marketers and creative directors (p. 1152)

Source	Focus	Summary	Relevant results	Method
	consumer engagement and consumer buying behavior (p. 1152)	and human feelings (p. 1152).	because ACC had a more vibrant and balanced impact in creativity (p. 1152). Additionally, ACC will increase sales due to this creativity (p. 1152).	
Chen et al. (2022)	Examination of AI used for marketing and communication (p. 125). Focus lays on voice-assisted AI and everyday interactions. (p. 125).	Consumers' multidimensional and relational interpretations of AI were mapped (functionality vs. emotion; human vs. machine comparison) (p. 125). Additionally, perception of voice-assisted AI and AI marketing communication were studied (p. 125).	Consumers` judgement of AI is connected to functionality and emotion, comparison and difference between AI and humans (p. 125). Furthermore, consumers see AI as unavoidable in marketing, but only bringing limited effects on product and brand evaluations (p. 125). Attitudes toward the effectiveness of AI marketing communication are neutral to slightly negative (p. 139)	In-depth interviews with 20 U.S. consumers (p. 130)
Brüns and Meißner (2024)	Perception of users toward brands that use GenAI for content creation is examined (p. 1). Effects of disclosure and the level of automation or assistance are examined.	The study tests whether the incorporation of GenAI in content creation by brands negatively affects reactions from users through reduced perceived brand authenticity. Study one measures credibility, electronic word of mouth, and loyalty for favorite brands of	Results for study one showed that automated use of GenAI for content creation caused negative reactions from followers (p. 5). It also had detrimental effects on perceived post	Experimental settings, controlled studies (p. 1)

Source	Focus	Summary	Relevant results	Method
		participants (pp. 4, 5). Study two examines whether people can identify whether content is created by AI or humans and how an AI-disclosure affects perceived authenticity, credibility, and brand attitudes (pp. 6-7). Study three adapts the design from study 1, but added an AI-assistance condition (p. 8)	credibility, EWOM intentions, and brand loyalty (p. 5). Study two showed that, even though users were not able to correctly identify ACC and HCC, content negatively affected brand authenticity, when it was disclosed (p. 7). Additionally, answers that followed after were more negative (p. 7). Nonetheless, the effect on EWOM was not significant (p. 7). Lastly, the findings of study three identified that the higher the level of AI-incorporation was, the more negative were participants' perceptions of authenticity, in addition to attitudes and behavior (p. 8)	
Aldous et al. (2024)	HCC vs. ACC using ChatGPT-4 is tested for cross-platform content creation (Facebook, Instagram, Twitter/X) (p. 376). Perceived adaptability, emotions,	Users judged paired ACC and HCC post versions of the same video, without knowing the source (p. 378). ChatGPT-4 was used to create platform-specific captions (p. 378). Finally, platform adaptability, emotional response,	Facebook: ACC performed better than HCC on all adaptability metrics, positive emotion, and all engagement metrics (pp. 379-380). Instagram: ACC as preferred regarding	Within-subjects user online study; Controlled survey experiment (p. 378)

Source	Focus	Summary	Relevant results	Method
	engagement, and preference when the content source is unknown were compared (p. 377).	engagement, and preference were measured (p. 378).	CTA and positive emotion; all other aspects were not significant (pp. 379-380). Twitter: ACC performed better on CTA and comments, the remaining metrics were not significant (pp. 379-380).	
Oh and Ki (2024)	Studies the effects of the role of agent type (human vs. AI Twitter bot) and tone of voice (conversational vs. organizational) on organization-public relationships (trust, satisfaction, commitment, control mutuality) and social media engagement intention on Twitter (p. 1)	Participants saw mock Twitter pages which consisted of identical tweets with manipulations of agent identity and tone of voice (pp. 4-5). Through this, it was tested whether switching from a human agent to an AI agent changes the perceived relationship quality and engagement intention by consumers, as well as whether a conversational human voice improves outcomes versus an organizational (impersonal) voice (pp. 4-5). Additionally, a possible interaction between agent and tone was studied (pp. 4-5).	Human-written tweets were preferred in regard to control mutuality when the tone is organizational, but no differences in trust, satisfaction, commitment, or engagement intention were found (p. 6). No difference between ACC and HCC was found when the tone was conversational (p. 6).	2x2 between subjects' experiment (p. 1); Twitter-based mock page experiment with 363 participants (p. 4)
Ali et al. (2025)	The focus of this study lies on the impact of GenAI adoption on brand authenticity, brand image, and self-	Hypothetical situations where restaurants were either using ACC and HCC on social media were presented to participants (p. 1). For every post, either an	Using ACC led to significantly lower perceived brand authenticity, image, and self-brand congruity, compared	Scenario-based experimental design (p. 4)

Source	Focus	Summary	Relevant results	Method
	brand congruity in the restaurant industry (p. 1). Additionally, the effects of these aspects on consumer behavior, including eWOM and behavioral intention (p. 1).	AI-disclosure or a human-disclosure was provided (p. 5)	to HCC (p. 1). Moreover, for ACC self-brand congruity emerged as the dominant driver of eWOM and behavioral intentions. Effects of authenticity and image effects were weaker (p. 7). In the HCC-condition, authenticity, image and congruity were all significant predictors (p. 7.)	
Kirkby et al. (2023)	This paper studied how consumers perceived brand voice authenticity, brand authenticity and brand attitude (p. 1108). The presented texts were disclosed as AI-generated or written by a human (p. 1108).	Adidas marketing texts with different levels of emotionality were presented to participants, labeled as AI-generated, human-written, or undisclosed (p. 1113).	The AI-disclosure had no negative effects on perceived authenticity, brand authenticity and brand attitude (p. 1108).	A 3x3 experimental design (p. 1108)
Jung et al. (2025)	Studied how AI-generated and AI-modified social media posts are perceived by users and how the AI label affects reactions to the content, the creator and the platform (p. 1). Additionally, it was investigated	14 participants discussed how they interpret AI-generated content and judged examples of social media posts that were labeled with „AI" (p. 1).	AI-labeled content was often interpreted as less authentic, more commercial or potentially deceptive (p. 4). Additionally, it was connected to lowered sincerity, especially for accounts which need to be considered as „original" (pp. 4-5).	Qualitative focus group study (five groups); user discussions were thematically coded (pp. 1,3)

Source	Focus	Summary	Relevant results	Method
	which way of labeling content is preferred (p. 1).		The importance of context was emphasized, as acceptance varied between the content types (p. 5). Self-applied disclosure labels were trusted more than labels applied by platforms (p. 5).	
Du et al. (2023)	The aim of this study was to gain a better understanding of how the incorporation of AI-generated content affects psychological and behavior user engagement and the role of emotion in this context (p. 121). Additionally, the labeling of ACC by firms is investigated (p. 121).	Texts and image components for the brand Nestlé were created using AI-tools (p. 125). Subsequently, two different manipulations were implemented in two different experiments (p. 125). In the first one, content with two different emotional appeals (high vs. low) was presented to participants (p. 125). In the second experiment, participants were either presented with AI-generated advertisements labeled as AI-generated or viewed the same ads without the label (p. 125). Ultimately, 428 valid responses were collected (p. 125).	AI-generated content had positive effects on psychological and behavioral engagement of consumers (p. 121). An AI-disclosure significantly affected user behavior engagement (p. 121).	Online experiments (questionnaires) (p. 121).

Note. Only studies that collected primary data from consumers, marketers or users of AI marketing tools were included. Conceptual papers, (literature) reviews, and technical studies were not included to ensure that human-centered perception of AI-generated content was the focus.

All in all, it is clear that the implementation of GenAI in the context of marketing and communication has become a highly relevant research field. Nonetheless, reactions from users depend on the context of the implementation. Previous studies indicate that perceived authenticity, credibility, and effectiveness of ACC depend on various situational factors (e.g. Aldous et al., 2024; Ali et al., 2025; Brüns & Meißner, 2024; Jung et al., 2025; Oh & Ki, 2024;). The study conducted by Du et al. (2023) revealed that ACC positively impacted consumers' psychological and behavioral engagement. In contrast, findings by Jung et al. (2025) showed that authenticity and sincerity ratings decreased after AI content was disclosed.

An aspect that reappeared in several studies relates to tone, voice and platform-specific adaptation. The study by Oh and Ki (2024) showed how the tone of communication can play a decisive, moderating role. In the context of organizational messages, a conversational, human-like tone can increase trust and engagement, regardless of whether it is ACC or HCC. Similarly, Aldous et al. (2024) found that ACC yielded engagement metrics that were just as good, or even better, than HCC, when users were not aware of the content source. These results suggest that it may be possible to align communication stylistically to make it seem human-like, which can compensate for the source, especially in algorithm-driven social media environments.

A third finding concerns the awareness of consumers and the sensitivity of context. If users are informed that content is created using GenAI, user engagement and ratings of authenticity decrease (Brüns & Meißner, 2024; Ali et al., 2025). In contrast, if consumers are not aware that content is created using GenAI, content can achieve comparable or better performance than HCC (Aldous et al., 2024). It was also shown that mere disclosure does not always negatively affect brand authenticity or attitude toward a brand, as long as the quality of content remains at a high level (Kirkby et al., 2023). These findings coincide with broader research, which shows that the intuitive ability to detect ACC is very limited and often based on flawed heuristics (Jakesch et al., 2022). Further results showed that openly communicating the implementation of AI in content creation or even the full automation reduces post credibility, brand trust and eWOM, especially through lower perceived brand authenticity (Ali et al., 2025; Brüns & Meißner, 2024). These mixed findings emphasize that the context and other factors, such as the message type, can influence how transparency regarding ACC can weaken or maintain authenticity, and that perceived sincerity and the message quality remain highly important Therefore, it seems that in controlled settings that specifically investigate the preference between ACC and HCC, the awareness of the content source might affect differences in perception more than the actual objective quality of the content.

While all studies provide valuable insights, they share one commonality: none of the studies were conducted in real-life marketing environments. The findings were derived from controlled experiments or hypothetical scenarios, where participants were presented with different versions of social media posts, had to judge imagined brand situations or other hypothetical scenarios. As the use of AI, more specifically GenAI, continues to grow in the field of marketing (Mohammadi & Jafari, 2024, p. 435), understanding how ACC is perceived and responded to by consumers in authentic, everyday contexts becomes increasingly important. Therefore, this study aims to address this gap, by investigating changes in user engagement, when consumers are not aware, whether the content they are viewing was created by humans or GenAI. In doing so, existing literature is extended by connecting AI-generated content to observable user engagement in real-life scenarios and does not merely rely on reactions to hypothetical scenes or stated intentions.

Research Questions and Hypothesis

When users actively decide to follow a brand account on Instagram, it can be assumed that this is because they enjoy the content, want to stay up-to-date or have a certain connection to the brand. In turn, through the posts published by a brand, users expect the output to satisfy their needs. These needs could be the wish to be entertained, learn more about the company or simply escape from reality (Whiting & Williams, 2013, p. 368). From a U&G perspective, engagement on Instagram posts can be seen as a reflection of whether sought gratifications were actually obtained. An additional aspect that needs to be considered is authenticity. As previously outlined, accuracy (whether someone is perceived as transparent in how they represent themselves) and connectedness (how engaged or familiar a consumer feels with a source) are both particularly relevant in order to appear authentic (Nunes et al., 2021, p. 3). Sudden changes in tone of voice or emotional warmth can disrupt the feeling of continuity that users associate with a brand's identity. If the tone and overall feel of text suddenly change in a way that does not feel familiar and a brand is not transparent about whether a human or AI wrote it, this could lead to brands being perceived as less authentic. In turn, drawing from the commitment-trust theory (Morgan & Hunt, 1994), a sudden loss of authenticity could decrease the trust users have in brands and make them question their commitment to the brand. While the commitment-trust theory was originally developed by Morgan and Hunt (1994) in the context of relationship marketing, with a physical presence as the norm, it remains applicable in this social media context. Trust and commitment are two highly relevant factors for maintaining strong relational exchanges with social media users, as their consistent support and engagement can be, among other aspects, attributed to these factors. While incorporating AI in content creation can increase work speed and personalization, it could potentially be problematic, if the output does not align with the centrally perceived brand values. For example, if ACC, that could seem impersonal, artificial, or inauthentic, is published, it could interfere with the public perception, if a brand normally embodies values such as authenticity or essentiality. According to the commitment-trust theory (Morgan and Hunt, 1994), this discrepancy in perceived values could lead to a decrease in trust among recipients and consequently reduced commitment.

All of these factors and the lack of studies in a real-life context lead to the overarching research question: How does AI-created content (ACC) affect user engagement compared with human-created content (HCC) on a real brand's Instagram channel? To gain more nuanced insight, two subordinated research questions are stated. The first one focuses solely on the difference between reactions to different content sources: How does user engagement differ between ACC and HCC on a brand account on Instagram? Engagement is a major motivator for brands to post and communicate on social media, as it can increase consumer loyalty (Hollebeek et al., 2024, p. 1). Hence, understanding how ACC and HCC differently affect engagement metrics is necessary in order to accurately judge whether GenAI can be incorporated in content creation. However, evidence is mixed. Previous studies revealed that when the source of the content is not disclosed and stylistic adaptation is high, ACC can perform equally well, or even better than HCC in terms of engagement (Oh & Ki, 2024; Aldous et al., 2024; Kirkby et al., 2023). However, these findings mainly reflect short-term reactions on isolated content pieces. Additionally, results from several studies were based on pure preference rather than behavioral engagement and did not account for already existing connections between brands and consumers. Especially for identity-driven brands that emphasize authenticity within their communication, incorporating GenAI in content creation on social media might be problematic, as other research shows that ACC can lead to a decrease in authenticity and willingness to engage, particularly when it is explicitly disclosed (Ali et al., 2025; Brüns & Meißner, 2024; Jung et al., 2025). Even if users might not actively recognize whether captions are written by AI, they still react to subtle changes in style, perceived warmth and social presence (Brüns & Meißner, 2024; Jung et al., 2025; Oh & Ki, 2024), all of which are cues that are central for maintaining trust (Gefen & Straub, 2003, p. 7). Since all these stated variables are key drivers in authenticity and trust, it is expected that

ACC reduces engagement, even if the content source is not immediately apparent.Therefore, the hypothesis is stated as follows:

H1: If social media content is created by AI instead of humans, it leads to lower user engagement.

For this study, content was divided into three categories - informative, promotional, and entertaining - which are commonly used and consistently identified as central content types among others in social media research. Previous research showed that these different types elicit engagement differently (Tellis et al., 2019, pp. 1, 11; Shahbaznezhad et al., 2021, p. 53). This can be explained from the perspective of the U&G theory (Katz et al., 1973a), which posits that each content type fulfills different needs and thus, addresses different gratifications sought, which could be either cognitive (learning through information), affective (enjoyment through entertainment) or utilitarian (rewards through promotion). Entertaining content, which fulfills hedonic or affective gratifications such as enjoyment or relaxation (Ashley & Tuten, 2015, p. 28; Hollebeek & Macky, 2019, p. 32), usually generates higher user engagement (de Vries et al., 2012, p. 85). Informative content, on the other hand, which aims to satisfy cognitive needs like knowledge or pre-purchase information (Muntinga et al., 2011, p. 27), often generates fewer shares, possibly because it can be perceived as dry (Tellis et al., 2019, pp. 1, 11). User engagement on these posts is interpreted as a sign of obtained gratifications. The engagement varies since each different type satisfies distinct needs to a different extent. From a U&G theory perspective, engagement can be an indicator of whether the gratifications were obtained. Simultaneously, the earlier chapter emphasized the crucial role of aspects like perceived authenticity or connectedness, which might carry different weight depending on the content type. If content is suddenly written by GenAI and not humans, it may affect user reactions differently, depending on the content type and gratifications obtained. While it could potentially have negative effects for user engagement with entertaining content, when the text suddenly feels less natural, informative content, which primarily aims to fulfill cognitive needs and where perceived connectedness may be secondary, might be less affected by GenAI-written captions, as long as the information remains relevant and clear. In contrast, Gu et al. (2024) found that creative and innovative ACC can increase consumers' perception of content, which, in turn, positively affected engagement (p. 2230). According to this, if entertaining content created by AI would be perceived as more creative, it could lead to increased user engagement.

Additionally, the aforementioned factors, accuracy and connectedness, could impact perceived authenticity differently, depending on the content type. A lack of connectedness could have stronger effects on AI-created entertaining content, whereas informative or promotional content might, as long as it is accurate and delivers what is promised, not perform worse in comparison to HCC. Prior research has delivered preliminary but inconclusive information about how ACC affects different content types. Hasan et al. (2024) found that entertaining content positively influences brand authenticity, but the question of how this changes when content is no longer created by humans remains. In addition, research also showed that reactions depend on different factors (Brüns & Meißner, 2024; Ali et al., 2025; Aldous et al., 2024). Lastly, all studies mentioned were conducted in controlled settings, therefore, it is unclear how this translates to real-world settings.

To investigate this, the second research question is stated as follows: Does user engagement differ across content types, and does this pattern differ depending on whether the content is human-created or AI-generated? In order to answer this question, since prior findings are conflicting, this study adopts an exploratory approach, and no hypotheses are formulated for RQ2.

These research questions are different but represent connected aspects that are important for understanding how ACC affects user engagement. While RQ1 focuses on a general difference in user engagement, RQ2 additionally considers how this preference varies across different content types. Studying these differences in a real-life-setting provides a more nuanced understanding of the context and reasons why ACC may lead to different user engagement than HCC. The following chapters will present the methods and results of this study, as well as discuss the findings, limitations, and give an outline for future studies.

Methods

Research Design and Rationale

To analyze the previously stated research questions, a quantitative field experiment was conducted. The social media platform Instagram was selected as the social media platform to conduct the experiment. This method design allowed the examination of real reactions from consumers as they browsed Instagram in their natural environment, without a prior experimental briefing or exposure instructions. Therefore, it offered a high external validity and a real interaction condition, since users are not aware that they were part of an ongoing study. Moreover, the platform is highly relevant for brand communication and development (Armstrong & Kotler, 2023, p. 480) and is one of the most used social media platforms globally (Statista, 2025b). It is acknowledged that a field experiment is invariably accompanied by limitations. These limitations areaddressed at a later point in this thesis.

As a theoretical basis for the relevant effects on consumers, three theories were chosen. The uses and gratifications theory (Katz et al., 1973a) explains why individuals select and use certain media, whereas the commitment-trust theory (Morgan and Hunt, 1994) emphasizes the importance of commitment and trust for establishing long-standing relationships between brands and customers. The concept of authenticity provides an additional aspect, which is highly relevant for brand-consumer-relationships. Each concept addresses key mechanisms such as interaction, trust, and consumer perception in the context of ACC and HCC.

To allow a comprehensive analysis, the following variables were selected: The independent variable in question one was "content source" (ACC vs. HCC) which is the main focus of this research question, whereas research question two additionally considered "content type" (informative, entertaining, promotional), to examine whether its effect varies across content types. To analyze textual characteristics, a coding scheme with predefined criteria was developed and each caption was coded accordingly (shown in chapter "Textual Characteristics of the Stimuli", Table 7). The present study relies only on measurable behavioral engagement, therefore, the dependent variable - user engagement - was measured in „number of views", „number of likes", „number of comments", „number of shares" and „number of saves". These metrics were selected, as they are commonly used and validated indicators for the level of intensity of user engagement on social media platforms (cf. Dolan et al., 2019; Schivinski et al., 2016). All posts were published from May to September 2025. The collection of engagement metrics was conducted exactly 7 days after each post was published, to ensure comparable numbers.

Field Experiment on Instagram

All posts were published on the Instagram account of Leica Camera Classics (@leica_camera_classic), which is a branch of Leica Camera focused on offering pre-owned and vintage cameras and accessories. The follower base is comprised of 14.2% from the United States, 6.7% from Germany, around 5% each from Italy, the United Kingdom, and France. The remaining followers are spread around the globe.

In total, 42 posts were published as 21 matched pairs. Half of them were accompanied by a caption written by ChatGPT-4o, while the caption for the other 21 posts were written by a human. The content was randomly assigned to each group of content source, to avoid systematic biases caused by the selected images, or the content quality.

Additionally, all posts from both categories were further categorized into promotional, informative, or entertaining content, to allow a better comparison. This classification was based on predefined criteria (cf. Content Types) which followed scientifically validated classifications in literature regarding CM (Dolan et al., 2016; Meire et al., 2019; Tellis et al., 2019). Every post with a caption from one content type (IV1; entertaining, informative, promotional) and content source (IV2; ACC, HCC) was followed by a second post with visually similar content with comparable composition and products (Figure 1). Thus, for every post there was a second one created which was comparable in terms of visual appearance and content. Using identical images and videos was not possible due to brand guidelines, therefore differences remained, which reflects the natural posting conditions.

Figure 1

Example of two paired visuals whose user engagement metrics will be compared.

Note. From Leica Camera Classics GmbH (2025)

These posts were published from May 15th to September 25, in a fixed rhythm of three posts uploaded per week, unless other posts had to be prioritized and shared. They were published on Tuesdays and Thursdays at 4:00 PM (CET) and Sundays at 6:00 PM (CET). The selection of these days was based on the posting schedule established for the Instagram account of Leica Camera Classics. Public holidays were not taken into consideration, because the account of Leica Camera Classics is a global one, not catering to just one country.

According to Instagram guidelines, it is necessary to indicate "photo-realistic videomaterial or real sounding audio, which was created digitally or manipulated, also with AI" with the AI-Info (Instagram Help Center, n.d.). This definition does not include texts for post captions, therefore, the AI-Info was not applied to the posts. This decision ensured that users were not biased when viewing the posts and thus allowed the conclusion that the measured metrics for user engagement were based on the caption and a residual risk of influence by the visual from each post.

Content Creation

The picture material consisted of high-quality product images and lifestyle photos and videos that were produced to be posted on Instagram during this experiment. The photos were mostly produced by an in-house photographer of Leica Camera Classics. Some photos and all videos were produced by the marketing manager of the company, who was in charge of writing the captions for the HCC category. The design of the content was done in accordance with guidelines defined by Leica Camera Classics. The pairs of photos and videos aimed to appear similar, with visually comparable products, comparable backgrounds, and, in case of videos, similar music and editing. Additionally, all visuals were created in a way in which key features that could influence engagement strongly were designed as similar as possible. This includes a similar number of products shown, background colors, and the length of videos. The goal was to create consistent atmospheric and visual conditions, so that variations in user engagement were primarily attributable to the caption source and not to differing visual design elements. While efforts were made to produce content that was as similar as possible across post pairs, certain differences were unavoidable. Due to the design of this experiment and its real-life setting, it was not an option to post identical visuals twice, as it would not be coherent with guidelines established by the Leica brand. This limitation will be addressed in more detail in a later chapter. Nonetheless, since personal preference in visual aesthetics and products varies among users, these deviations are not considered problematic. While some users could have preferred one visual, others might have preferred another one. This aspect simply underlines the ecological validity of the experiment, as it was conducted in a real-world setting.

For the purpose of this study and the focus on user engagement within brand communication, content was divided into three categories: (a) informative; (b) entertaining; and (c) promotional. Based on previously stated literature, the different content types were defined as follows. Posts within the category of informative content provided users with relevant and interesting information, facts about the history of the product, or explanations about the products or the services shown in the post. The intention was to give users a reason to follow the account by stimulating interest and educating them. Entertaining content was defined as light-hearted, easy-to-understand and playful posts that primarily aimed to provide users with a pleasurable experience while incorporating the brand's available products or services. Promotional content included posts that highlighted products or services with the explicit intention of promoting them, aiming directly to increase sales. In this study, promotional posts potentially included persuasive elements like scarcity, urgency, or direct

CTAs, which encouraged users to visit the (online) shop or engage with the content. The selection of products shown in the photos heavily depended on the content type. Table 5 provides an overview of the selection criteria used to categorize the choices.

Table 5

Selection criteria for products and topics depending on the content type.

Content type	Selection criteria	Reasoning
Informative	Products or topics with a high level of informational potential or with an interesting background story.	These posts should provide users with interesting information, historic facts, and technical details, by which an added value is offered by following the account.
Promotional	Products or topics that had to be promoted.	The goal was to increase visibility of topics and sales of products by strategically positioning them in the focus of the relevant target group.
Entertaining	Products or topics that had not been shown for a longer time or that fit well into a pre-established content idea.	The aim was to create variety in the products shown and topics addressed, and to continue existing series of topics in an entertaining, light-hearted way.

Note. This table summarizes the selection criteria for the product or service chosen for each content type during the creation of the stimulus material. All items were selected in accordance with these criteria and the availablitity of the brand's assortment.

To make the present experiment more realistic, and since posting a contest or discounts every week was not an option, the definition of promotional content was simplified and adapted. This allows a scientifically correct comparison between content types and sources. Therefore, in this study, promotional content refers to any type of brand-generated post that actively and directly promotes a specific product, platform, or service. This content type often explicitly mentioned products, commercial offers, calls-to-action or other sales related messages. Through this, it aims to encourage purchases or other transactional behavior. To summarize, promotional posts are primarily designed to activate consumer responses that align with the brand's marketing objectives, which could be driving traffic, product awareness, or conversions. This definition is consistent with already existing literature, which defines promotional posts as the ones that aim to achieve immediate marketing outcomes.

Prompt Engineering

Prompts are what make interaction between a user and a LLM possible (Gao, 2023, p. 1). It considers the method of wording tasks for the AI in a way so that the output is exactly what is asked for. Often this prompt is included in the input, given as a direct order, without explicitly naming the task (Giray, 2023, p. 2629). Simplified, the input you give to language models, aiming toward a specific output, is a prompt, and it consists of different elements, which are instruction, context, input data, and an output indicator (Giray, 2023, p. 2630). These elements serve as specifications for creating a prompt that generates the desired outcome. Giray (2023) defines these four components as follows: "Instruction" refers to the overall task that gives the direction to the needed output (p. 2630). Circumstantial information that gives required background information is considered as "context", while the "input data" is the root topic that should be answered or addressed by the AI-tool and provides a deeper understanding to the model (p. 2630). Lastly, the "output indicator" includes details about the desired result (p. 2630). It is necessary to include these elements so that the intentions are clearly communicated to the model (Giray, 2023, p. 2630).

All captions created using AI in this experiment were written by ChatGPT-4o. The selection of this model was justified by the fact that ChatGPT is provided by the company to all employees, so the internal company version was used. The aim of this study was to test the theoretically derived hypotheses and establish implications for practice. As this experiment was conducted in a real setting, the content created with AI needed to comply with company-specific requirements, such as a specific tone of voice. Therefore, before any captions were created, an analysis of the writing style from previous captions was conducted. For this, nine captions written by the person responsible for social media content creation at Leica Camera Classics were analyzed by ChatGPT-4o.

Simultaneously, ChatGPT-4o was asked to write an effective prompt to use for writing engaging Instagram post captions. Additionally, the model was asked to, according to each content type, act as a social media manager and reflect the latest trends when writing the captions. The first version of the prompt was the following:

Here's the photo 📸 (uploaded). This is a promotional post for my new candle collection launching next week. I want the caption to be playful and a bit cheeky but still chic. Audience is millennial women who love home decor. Use my style from previous captions. (OpenAI, 2025).

To enhance clarity and create a standardized prompt template, this first draft was adapted. The final prompt was the following:

> Here's the photo/video of a [insert shown camera]. Use my style from previous captions for [informative/promotional/entertaining] content as a reference and, as an expert on social media, write a caption in English, that is fitting to use for an Instagram post and promises a good performance.
> Here is additional information you can use for the caption: []. (OpenAI, 2025).

Making sure that this prompt would include all elements required according to Giray (2023), the prompt was divided into the four categories (Table 6).

Table 6

Components of final prompt assigned to the four necessary prompt elements

Prompt element	Text passage from prompt used for this study	Reason
Instruction	„…write a caption in English…promises a good performance"	Defines the task and the goal.
Context	„Use my style from previous captions…" and „Here is additional information…"	Offers background information for style and content.
Input data	„Here's the photo/video of a [insert shown camera]"	Content basis, for which the output is produced.
Output indicator	„write a caption in English…for an Instagram post…"	Determines format and language of output

Note. This table shows how all needed elements of a prompt defined by Giray (2023) were provided within the final prompt used in this study.

To ensure ChatGPT-4o understood the desired outcome and what was meant by "a good performance", it was asked how it interpreted this phrase. The answer was the following:

> Write a caption that fits my tone and visual identity, gives value to my followers, and is structured in a way that supports attention, saves, shares, comments, and clicks—without compromising the professional and composed nature of my brand. (OpenAI, 2025).

Since this experiment was conducted using a real Instagram account of a brand, where all posts needed to comply with specific guidelines, it was decided that all initial captions which are produced by ChatGPT-4o could be revised once, as it is recommended to always examine the output before publishing it (Tamkin et al., 2021, p. 7) and all posts ultimately needed to be in line with brand guidelines. This meant that after the initial prompt, if needed, a second one with small necessary changes could be given. This ensured all captions remained in line with the brand, while still being classified as “created by AI”. Furthermore, minimal adjustments by a human were executed. This included changing all em dashes (—) to regular hyphens (-). Em dashes have almost become an indicator for AI-written content. In order to avoid biases because users might recognize these formatting-specific patterns, it was decided to change them accordingly. Additionally, factual errors were corrected. Here only minor alterations were made, such as changing the term “designations” to “technologies”. This approach ensured that captions written by ChatGPT could still be considered “AI-created”, as they did not alter the structure, tone, or stylistic characteristics produced by AI, while also complying with company guidelines regarding content and stylistic requirements.

Textual Characteristics of the Stimuli

The stimulus material consisted of 42 posts that were published on the brand’s Instagram account. These posts served as the material to investigate differences in user engagement depending on whether the caption was created by AI or a human. The posts were uploaded from mid-May to the end of September. Additionally, the posts were divided into three content types, informative, entertaining, and promotional, with seven posts per category for each content source. To systematically collect relevant textual features of the captions, a coding scheme (Table 7) was developed. These features were meant to capture structural, stylistic, and interactive aspects that could influence user engagement. This ensured a consistent and comprehensive basis for the comparison of data. The coding was performed by one person.

Table 7

Coding scheme for the analysis of Instagram captions

Category	Code / Values	Description	Scale Level
Caption length	1 = short (≤52 words) 2 = medium (53-85 words) 3 = long (>85 words)	Count all words separated by spaces to determine text length.	Ordinal
Call-to-action (CTA) present	0 = no 1 = yes	Indicates whether the caption includes an explicit prompt to act (e.g., buy, follow, comment).	Dichotomous
Emojis present	0 = no 1 = yes	Coded as 1 if at least one emoji is included in the caption.	Dichotomous
Direct address to reader	0 = no 1 = yes	Indicates whether users are directly addressed (e.g., "you", "your", "tell us").	Dichotomous
Question present	0 = no 1 = yes	Indicates whether the caption contains a question (recognized by a "?").	Dichotomous
Number of hashtags	Numeric value (e.g., 0, 1, 2, …)	Counts the number of hashtags contained in the caption.	Metric

Note. Each caption is one coding unit.

To get an overview of the stimulus material, descriptive statistics were calculated. As shown in Table 8, on average, captions created by AI were longer than the ones written by a human. Additionally, with an average caption length of 68 words for HCC and 81 words for ACC, most captions were likely longer than 125 characters. CTAs were less frequent in HCC compared to ACC. Emojis were used in the majority of captions of both conditions, and the same is true for directly addressing the reader. A little over half of the AI-created captions also contained a question, while only a third of human-written ones did. Lastly, the average number of hashtags used was higher in HCC.

Table 8

Descriptive statistics of captions textual characteristics by content source

Category	HCC (n = 21)	ACC (n = 21)
	M (*SD*)	*M* (*SD*)
Caption length	67.7 (38.8)	80.8 (39.6)
CTA present	19.0%	52.4%
Emojis present	85.7%	71.4%
Direct address to reader	71.4%	76.2%
Question present	33.3%	57.1%
Number of hashtags	6.71 (1.49)	5.43 (1.78)

Note. *M* = Mean; *SD* = Standard deviation. The percentages represent the respective proportions of captions containing the specific feature within each content source.

[a] Caption length is *m*easured by the number of words in the caption.

These textual characteristics offer detailed insights into the captions and lay the groundwork for further analysis of how ACC and HCC differ stylistically and whether these differences are connected to the engagement results.

Data Collection and Engagement Metrics

For the purpose of this study, as a theoretical basis for measuring engagement, the theoretical model of Schivinski et al. (2016), which is based on the "Consumer's Online Brand-Related Activities"-framework from Muntinga et al. (2011), was chosen. This model differentiates between consumption, contribution, and creation (Schivinski et al., 2016, p. 66). For the purpose of this present study, only the quantitative interaction metrics "view", "like", "comment", "save" and "share" were considered. Since these metrics do not include content creation by users, the dimension "creation" in the original sense of Schivinski et al. (2016) was excluded. Thus, the analysis was based on categories "consumption" (views) and "contribution" (likes, saves, shares, and comments) of this model, with all variables listed in Table 9. This decision allowed the study to use the underlying framework, while simultaneously adapting the operationalization to the available empirical data and clearly stating the non-consideration of the third dimension as a limitation of this study.

Table 9

A short description of the collected engagement metrics.

Engagement metric	Description
Views	Number of all views on the Instagram post (views on Facebook were excluded)
Likes	Number of likes of the post, not counting any likes from comments
Comments	Number of comments under each post, excluding responses by the brand itself
Saves	Number of saves of the post
Shares	Number of shares on personal story as well as private chats

Note. This overview includes all engagement metrics that were collected for each post from Instagram insights.

The engagement metrics were carefully collected from Instagram Insights and written down in an Excel sheet. This was done manually, always seven days after each post was published. For every post, a screenshot from the relevant numbers in Instagram Insights was taken. After all numbers belonging to one post were written down, they were checked again to ensure no mistakes were made. Before the analysis of the data, all numbers were checked for completeness.

Data Analysis Strategy

This study followed a quantitative, content-analytical research approach to examine the differences in user engagement between ACC and HCC in social media posts. The independent and dependent variables, along with the textual characteristics, were imported to RStudio. Descriptive statistics, such as means and standard deviations, were calculated to get a general first impression of how the posts performed on average. Subsequently, the dataset was checked for outliers and their influence. This was done by creating a boxplot of all engagement metrics to visually identify potential outliers. Afterwards, descriptive statistics were calculated for HCC and for ACC with and without the outlier post that drastically outperformed all other posts in almost all metrics, to see how the descriptive statistics would change. However, the outlier post was still included in later data analysis, to avoid manipulating engagement patterns that can naturally occur on social media. To get a more nuanced understanding of the data, descriptive statistics were also calculated for all content types.

The aim of this data analysis was to identify different reactions from users, to better understand the impact of ACC in real social media contexts, test the hypothesis and address the defined research questions. Therefore, to answer research question one, content source (ACC vs. HCC) was considered as the independent variable, while user engagement metrics (likes, comments, shares, views, and saves) were the dependent variables. Before comparing the two groups, the normality for the dependent variables was tested with a Shapiro-Wilk test. Since most results showed a non-normal distribution of the dependent variables and the sample size was rather small, a non-parametric test was selected. Since homogeneity of variance is not required for a Mann-Whitney-U test, no Levene's test was calculated.

For the second research question, content source was considered as the independent variable again, in addition to content type, the second independent variable (informative, entertaining, promotional). Engagement metrics remained as the dependent variables. Again, the assumptions of normality were tested using a Shapiro-Wilk test since the structure of the data and the number of groups were different. Since this assumption was violated again and the data involved two independent variables with multiple levels, an Aligned Rank Transform (ART) ANOVA was performed to conduct a non-parametric factorial analysis and test the interaction. To further explore research question two, a separate Kruskal-Wallis test was performed to compare all engagement metrics for all three content types within both content sources. This allowed to understand whether content type mattered within each source, independent of interactions.

As additional factors that might have different effects on ACC and HCC, two of the textual variables were chosen for further analysis. Since the amount of CTAs and questions used in captions differed strongly between ACC and HCC, Mann-Whitney U tests were conducted to see if they affected user engagement within the content source categories differently.

Results

Contextual Account Performance

Before calculating the descriptive statistics, the general performance of the Instagram account of Leica Camera Classics was analyzed. The timeframe for the analysis was set to the mid of May to the end of September, the exact timeframe when the content for the experiment was uploaded. The metrics from this timeframe were compared to the metrics from January 1st to

May 14th. Additionally, these numbers include not only posts, but also stories. Nonetheless, since more content created by the brand is published in the feed compared to stories, these numbers provide relevant insight. Views and content interactions (e.g. likes, comments, reactions on stories) increased by 100%. In contrast, account visits decreased by 26.2%, follows by 4.6% and reach fell by 65.7%.

Descriptive Statistics

In order to get a general overview of how all 42 posts were performing on average, mean and standard deviation were assessed for all engagement metrics and can be seen in Table 10. The relatively high standard deviations for likes, saves and views indicate a partially strong variance in post performance.

Table 10

Descriptive statistics for engagement metrics across all posts

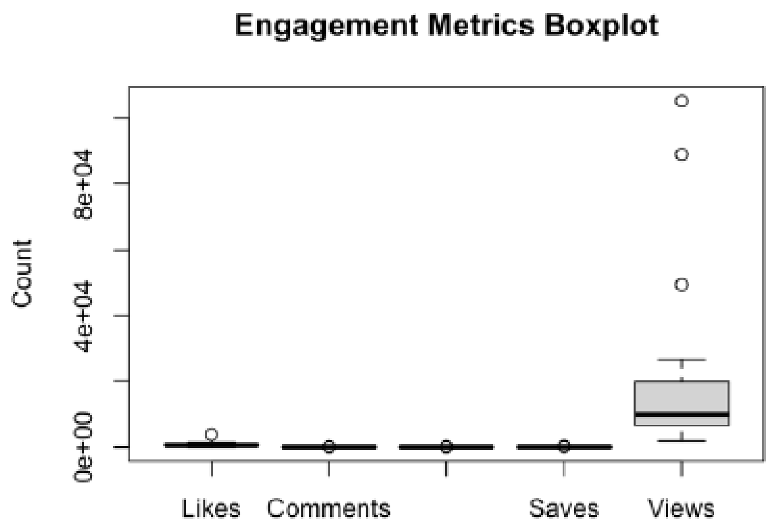
Engagement Metric	*M*	*SD*
Likes	721.60	576.29
Comments	6.21	6.98
Shares	6.33	13.69
Saves	34.40	41.78
Views	16547.38	20301.77

Note. *M* = means; *SD* = standard deviation

In order to identify potential outliers that could have distorted the results, a boxplot was created (Figure 2). This showed that a few posts received exceptionally high engagement metrics, with one particular post, number 25, which outperformed all other posts in likes, comments, shares and saves. Since this AI-created post received an unusually high number of views, it can be assumed that it went viral or was seen as particularly interesting by the Instagram algorithm. This could be related to a particularly favorable combination of different factors like timing, visual appeal or the caption. Though the exact cause cannot be determined, its good performance is not an exclusion criterion for the following analysis, as such posts are a natural part of social media dynamics. To see how the results would change, if there had been no outlier, a table with descriptive analysis was calculated for ACC. When post 25 was excluded, engagement decreased across all metrics, with *M* = 604.35 (*SD* = 308.73) likes, *M* = 4.75 (*SD* = 5.75) comments, *M* = 2.90 (*SD* = 1.80) shares, *M* = 27.60 (*SD* = 17.32) saves, and *M* = 11,981.45 (*SD* = 10,341.96) views. Nonetheless, varying user engagement on posts is a natural occurrence on social media, therefore, post 25 was included in further tests.

Figure 2

Boxplot of engagement metrics across all posts



In order to get a more nuanced understanding of user engagement and post performance between the two content sources, descriptive statistics were calculated for all engagement metrics, distinguishing between ACC and HCC (Table 11). The results showed that, on average, posts with human-written captions received slightly more comments and tended to be viewed more often. In contrast, posts with captions written by AI achieved more likes and were shared and saved with a higher frequency. The relatively high standard deviations also indicate that the individual posts varied considerably in received user engagement.

Table 11

Descriptive statistics for engagement metrics by content source (ACC vs. HCC)

Engagement metric	HCC *M*	HCC *SD*	ACC *M*	ACC *SD*
Likes	690.05	351.09	753.14	745.30
Comments	6.24	5.00	6.19	8.66
Shares	5.71	5.94	6.95	18.65
Saves	29.57	19.99	39.24	55.94
Views	17446.48	21430.50	15648.29	19595.09

Note. *M* = mean; *SD* = standard deviation

Lastly, to better understand the collected data in regard to different content types, descriptive statistics for engagement of the different content types were calculated. Table 12 shows that informative content achieved the highest number of likes, shares, saves, and views, while entertaining content received the most comments.

Table 12

Descriptive statistics for engagement metrics by content type

Engagement Metric	Entertaining		Informative		Promotional	
	M	*SD*	*M*	*SD*	*M*	*SD*
Likes	582.50	706.21	876.07	330.25	273.81	903.66
Comments	7.00	5.29	6.36	7.59	3.75	8.98
Shares	4.43	3.36	11.21	3.80	2.13	23.08
Saves	21.21	33.29	48.71	12.74	13.90	68.85
Views	10576.86	12984.50	26080.79	6438.69	6598.91	32633.65

Note. *M* = mean; *SD* = standard deviation

Comparison of ACC and HCC

Research question one highlights the differences in user engagement between ACC and HCC. By calculating descriptive statistics, this question has been partially answered. The results showed that, if all posts were included, posts published with a caption written by ChatGPT-4o outperformed posts with human-written captions in every metric except for views. When post number 25, the one with exceptionally high engagement metrics in four of the five engagement metric-categories, was excluded, HCC outperformed ACC.

To test normality, a Shapiro-Wilk test was conducted for each engagement metric separately for ACC and HCC. Likes were normally distributed for HCC ($W = 0.97$, $p = .714$), but not for ACC ($W = 0.6$, $p < .001$). All other engagement metrics also deviated from normality. Comments were distributed non-normally for both HCC ($W = 0.87$, $p = .011$) and ACC ($W = 0.585$, $p < .001$), as well as shares in HCC ($W = 0.72$, $p < .001$), and ACC ($W = 0.305$, $p < .001$). Saves violated normality in HCC ($W = 0.90$, $p = .035$) and ACC ($W = 0.505$, $p < .001$) and views showed strong deviations in HCC ($W = 0.54$, $p < .001$) and also ACC ($W = 0.579$, $p < .001$).

Due to the non-normal distribution of engagement metrics and the small sample size, no Levene's test was calculated and instead a Mann-Whitney U-test was chosen immediately to further analyze the difference in user engagement between ACC and HCC. The results showed no significant differences between the two content sources in likes ($W = 202$, $p = .651$), comments ($W = 189.5$, $p = .440$), shares ($W = 156.5$, $p = .107$), saves ($W = 224.5$, $p = .930$), or views ($W = 187$, $p = .406$). Engagement distributions between posts with human-written and AI-written captions were very similar across all metrics, which indicates that posts with captions from one content source did not systematically outperform those generated from the other.

In conclusion, both the descriptive statistics and the Mann-Whitney U-test showed no strong differences between engagement metrics for ACC and HCC. This means that posts from both content sources did not differ in their ability to generate user engagement on posts published by the brand on Instagram. For likes, comments, shares, saves, and views, no statistically significant results were found.

Influence of Content Type

As a next step, an analysis for research question two was conducted. Normality was checked for all subgroups, combining content source and type for each engagement metric. The results (Table 13) showed that in various combinations, the assumption of normality was violated. These deviations were particularly clear for promotional content, where several tests were significant. Comments and shares in entertaining content also violated the assumption, and only a few subgroups within informative and entertaining content were distributed normally. Therefore, since the assumption of normality was not consistently fulfilled across all cells of the factorial design, the Levene's test was omitted, and a non-parametric procedure was used for further analysis. Specifically, the ART ANOVA was chosen, because this method tests main effects and interactions between factors robustly, even when normality is not given.

Table 13

Shapiro–Wilk Normality Tests by Content Type and Content Source

Engagement metrics	Content type	Content source	W	p
Likes	Entertaining	ACC	0.81	0.057
Likes	Entertaining	HCC	0.95	0.721
Likes	Informative	ACC	0.92	0.486
Likes	Informative	HCC	0.94	0.608
Likes	Promotional	ACC	0.71	0.005*
Likes	Promotional	HCC	0.934	0.624
Comments	Entertaining	ACC	0.65	0.001**
Comments	Entertaining	HCC	0.75	0.012*
Comments	Informative	ACC	0.89	0.282
Comments	Informative	HCC	0.84	0.090
Comments	Promotional	ACC	0.53	< .001***
Comments	Promotional	HCC	0.81	0.052
Shares	Entertaining	ACC	0.91	0.400
Shares	Entertaining	HCC	0.83	0.081
Shares	Informative	ACC	0.82	0.062
Shares	Informative	HCC	0.92	0.453
Shares	Promotional	ACC	0.49	< .001***
Shares	Promotional	HCC	0.72	0.006**
Saves	Entertaining	ACC	0.97	0.901
Saves	Entertaining	HCC	0.98	0.934
Saves	Informative	ACC	0.97	0.917
Saves	Informative	HCC	0.94	0.674
Saves	Promotional	ACC	0.67	0.002**
Saves	Promotional	HCC	0.8	0.037*
Views	Entertaining	ACC	0.89	0.268
Views	Entertaining	HCC	0.99	0.994
Views	Informative	ACC	0.81	0.048*
Views	Informative	HCC	0.88	0.235
Views	Promotional	ACC	0.76	0.017*

Engagement metrics	Content type	Content source	W	p
Views	Promotional	HCC	0.64	0.001**

Note. Values of $p < 0.05$ indicate a deviation from normality.

*$p < .05$. **$p < .01$. ***$p < .001$.

The ART ANOVA was performed for all engagement metrics to analyze main and interaction effects. For likes, no significant main effect of content type ($F(2, 36) = 0.64$, $p = .536$) or content source ($F(1, 36) = 0.03$, $p = .856$) was found. The interaction between these independent variables was also was not significant ($F(2, 36) = 0.22$, $p = .803$). No significant main effects were found for content source ($F(1, 36) = 0.60$, $p = .442$) and content type ($F(2, 36) = 0.29$, $p = .752$), as well as the interaction between both ($F(2, 36) = 1.10$, $p = .343$) with regard to comments. For shares, no significant effects of content type were found ($F(2, 36) = 0.40$, $p = .676$). The same applies to main effects of content source ($F(1, 36) = 0.22$, $p = .641$) or the interaction between both ($F(2, 36) = 0.59$, $p = .560$). The result stayed consistent, as no significant main effect of content type on saves emerged ($F(2, 36) = 2.40$, $p = .105$), as well as no significant effect of content source ($F(1, 36) = 0.87$, $p = .357$) or interaction between both ($F(2, 36) = 0.65$, $p = .526$). Lastly, for views, the ART ANOVA found no significant effect of content type ($F(2, 36) = 0.35$, $p = .708$), content source ($F(1, 36) = 0.19$, $p = .663$) or interaction ($F(2, 36) = 0.02$, $p = .985$).

In summary, across all engagement metrics no measurable effect of content type, content source, or the interaction of both was found during the inferential analysis. Due to the insignificance of the results, no post-hoc test was carried out. This absence of interaction effects suggests that the relative performance between posts with AI-generated captions and the ones with human-written captions does not vary between different content types.

Explorative analysis

To further explore potential effects of content type on engagement metrics within both content sources, separate Kruskal-Wallis tests were performed for HCC and ACC. The results showed no significant differences between entertaining, informative, and promotional posts. For likes, no significant differences were found in ACC ($\chi^2(2) = 0.39$, $p = .825$) and HCC ($\chi^2(2) = 1.07$, $p = .586$). For comments, also no significant differences appeared (ACC: $\chi^2(2) = 3.11$, $p = .211$; HCC: $\chi^2(2) = 0.83$, $p = .662$). The same outcome appeared for shares (ACC: $\chi^2(2) = 0.91$, $p = .633$; HCC: $\chi^2(2) = 0.63$, $p = .729$), saves (ACC: $\chi^2(2) = 1.17$, $p = .556$; HCC: $\chi^2(2) = 3.37$, $p = .185$), and views (ACC: $\chi^2(2) = 1.10$, $p = .577$; HCC: $\chi^2(2) = 0.23$, $= .891$).

In summary, these exploratory analyses show that within each content source, content type does not have a systematic influence on engagement. These results also support the findings from the ART ANOVA, which showed that no main or interaction effects involving content type were present in this study.

To further analyze differences between AI-written captions and human-written ones, the connection between specific textual variables and engagement metrics was tested. The difference in the presence of a CTA in HCC (present in 19%) and ACC (present in 52.4%) called for further calculations, to see whether the presence was associated with differences in user engagement. Therefore, separate Mann-Whitney U tests were conducted for ACC and HCC. Table 14 shows the results with W and p-values for each engagement metric for both content sources. Across all engagement metrics in both content sources, no significant results were found between posts containing a CTA and those that did not.

Table 14

Results of a Mann-Whitney U tests comparing posts with and without a CTA in the caption.

Engagement metric	Content source	W	p
Likes	ACC	54	0.972
	HCC	28	0.622
Comments	ACC	67	0.414
	HCC	29.5	0.718
Shares	ACC	42.5	0.390
	HCC	31.5	0.857
Saves	ACC	49.5	0.725
	HCC	27.5	0.591
Views	ACC	48	0.647
	HCC	18	0.165

Note. The analyses were conducted separately for ACC and HCC. Exact p-values could not be calculated due to tied ranks.

Another textual variable that differed between ACC and HCC was whether the captions included a question. Only 33.3% of captions written by a human included a question, compared to 57.1% of captions written by AI. To investigate whether there was a connection between included questions and the engagement metrics, Mann-Whitney U tests were calculated for ACC and HCC separately (Table 15). The only significant result found was for posts with ACC, where captions that contained a question received significantly more comments than those without. In comparison, for posts with HCC this effect was marginal. Other than that, no significant effects were found for likes, shares, saves, or views.

Table 15

Results of a Mann-Whitney U tests comparing posts with and without a question in the caption.

Engagement metric	Content source	W	p
Likes	ACC	42	0.414
	HCC	36	0.351
Comments	ACC	14.5	0.005**
	HCC	24	0.066
Shares	ACC	62.5	0.563
	HCC	47	0.91
Saves	ACC	41	0.374
	HCC	43.5	0.709
Views	ACC	48	0.696
	HCC	43	0.682

Note. The analyses were conducted separately for ACC and HCC. Exact p-values could not be calculated due to tied ranks.

**p < .01.

Discussion of Results

Summary of key findings

Taking a closer look at the general performance of the account, the results are mixed. It is important to note. that during this time, the posting frequency was increased from one to two posts per week to three posts per week. This may partially explain higher engagement metrics such as views or interactions. What is surprising about this outcome is that, while views and content interactions increased, reach and profile visits decreased.

Various factors could explain these differences, such as changes in the Instagram algorithm. Seasonal effects could affect user activity and exposure to the content, while changes in user browsing habits might explain fluctuations in visits. The increased posting frequency naturally increases views, so it is difficult to attribute the rise exclusively to ACC. Analysis of the textual variables showed that ACC included questions in the captions almost twice as often as HCC. Since questions can simulate user responses, part of the increase in interactions might be explained by the higher number of questions in ACC captions. As Bowden (2009, p. 65) stated, the process of engagement affects new and existing audiences differently. Therefore, higher interactions may come from existing followers who already had established a relationship with the brand, rather than new audiences.

The higher engagement with the content but simultaneous lower reach could indicate a stronger engagement within a smaller audience segment. Additionally, decreased profile visits could be interpreted in two different ways, (a) users were more satisfied with content and did not need to explore additional content on the profile, or (b) users were not interested in viewing more content of the brand, and therefore did not visit the profile.

In summary, it is clear that the observed changes cannot be attributed solely to the newly introduced content source. Nonetheless, this overview provides valuable contextual insights that should be taken into account when ultimately assessing the effect of the incorporation of AI in content creation on social media.

Both research questions were addressed using different statistical tests. To answer the first one, which concerned the different effects between posts with AI-generated captions and human-written captions on engagement metrics, the Mann-Whitney U-test showed no statistically significant differences across any engagement metrics. Therefore, in the context of this study, AI-generated captions did not perform better or worse than human-written ones with regard to user engagement. As a result, the hypothesis was rejected.

To answer research question two, which followed an explorative approach, the analysis likewise revealed no evidence that indicated content type affected user engagement. Moreover, no interaction effects between content type and content source were identified, which indicates that the relative performance of ACC did not depend on a specific content type. Although descriptive statistics showed variations in user engagement, ultimately none of the differences reached statistical significance. In further explorative analysis, a Kruskal-Wallis test was conducted separately for ACC and HCC, aiming to explore potential differences within the two content sources. The lack of significant differences between entertaining, informative and promotional posts for any metric coincides with the findings from the ART ANOVA. These results show that content type did not have a measurable influence on user engagement within either ACC or HCC posts. Even though prior research found increased engagement for entertaining content, the absence of the difference might be due to the small sample size, the strong visual impact of the picture or video, or other platform-specific factors.

Overall, these findings suggest that neither the content source nor the content type had a measurable impact on user engagement in this real-life context of this study. Since engagement always fluctuates on social media due to factors such as algorithmic distribution, timing of posting or users' individual perception of relevance, these contextual factors could have potentially contributed to the non-significant differences, even though descriptive statistics indicated moderate variation. Also, after excluding the outlier, descriptive statistics only showed minimal differences between HCC and ACC, which further supports this.

To further explore potential associations between factors, Mann-Whitney U tests were calculated to analyze differences between posts with ACC and HCC. Due to the large difference in use of CTA and questions in the captions between the two content sources, the effect of the presence of these textual variables on engagement was tested for both content source categories. The Mann-Whitney U test for the effect of CTAs in captions showed no significant influence on engagement metrics. Neither likes, comments, shares, saves, nor views were significantly different between posts with and without a CTA. The results applied for both AI-generated and human-written captions. The lack of significant differences across engagement metrics for both ACC and HCC indicates that the inclusion of CTAs did not systematically affect user engagement. To summarize, this means that, in this specific setting, the presence of a CTA was not associated with higher engagement and did not provide detectable additional benefits for user engagement. A possible explanation for this is that CTAs are widely used on social media and might not get as much attention anymore due to that, especially in regular posts without a clear incentive. Additionally, the effects of a CTA might depend more on the users' interest in the topic of the post and the personal relevance.

The same analyses were performed for the textual variable "Question present". Here, the results were more differentiated. The results showed that using questions in post captions significantly increased the number of comments, but only for posts with captions written by AI. For posts with human-written captions this effect was marginal and not statistically significant. The findings suggest an increased effectiveness of questions in ACC, possibly because they offer a more interactive aspect to the regular writing style of GenAI and therefore increase users' motivation to reply. Therefore, questions in AI-generated captions might be used strategically to increase comments on posts, while other engagement metrics are not affected. However, this is a speculative interpretation, which would need to be tested in future research. These results provide a foundation for the following section, which situates them within existing research and relevant theoretical frameworks.

Interpretation in Light of the Theories

The results of this study showed no significant difference in user engagement between ACC and HCC. Previous studies, which examined the effect of ACC on users and on their engagement, have shown that an AI-disclosure can lower authenticity, willingness to engage, make the brand seem less credible and decrease trust (Brüns & Meißner, 2024; Ali et al., 2025). As no drop in engagement was found in this present study, which was conducted in a real-life setting, the findings suggest that an AI-disclosure may be an important factor that moderates user engagement.

In contrast to this, other research has found that AI-generated content can perform similarly to human-created content, especially when the writing quality is high (Kirkby et al., 2023), which would align with the findings, as only revised content that fit the brand's quality standard was ultimately published. Another finding which supports similarity between ACC and HCC was that the output of AI-generated content can match HCC when it was aligned with platform norms (Oh & Ki, 2024). When no AI-disclosure is given, tone and structure might matter more than authorship. Hence, the posted captions written using AI likely followed Instagram conventions and matched the company's tone of voice, which also supports the similarity in engagement metrics between both content sources.

As posts with AI-created captions were uploaded without any disclosure about the content source, the users' attention was not focused on questioning the content source or actively judging the quality of the caption. Even though Jakesch et al. (2023) showed that humans have difficulties in detecting AI-generated text, this might not be transferable to social media contexts. As the study by Jakesch et al. (2023) required participants to judge self-presentations from sources that were entirely unfamiliar to them, the findings cannot indicate whether followers of a brand would notice a shift to AI-generated texts, because a certain prior relationship already exists. Therefore, changes in content production can be both more or less detectable. Additionally, it is not only followers who view the posts, which can add another layer of complexity in predicting user engagement on ACC. Often, the engagement depends more on users' perceptions rather than the actual source, therefore, even though half of the captions were written by AI, user engagement remained relatively unchanged. This implies that engagement relies more on the users' perception of quality and less on authorship, which is supported by the non-significant results for research question one.

Since authenticity plays a significant role in brand communication, preserving it is essential. Results showed that ACC achieved similar user engagement as HCC, which can be interpreted as an absence of negative user reactions to the content. This might be because the captions written by AI kept a consistent brand voice, informational clarity, as well as an emotional, non-robotic tone. Additionally, it might be that the visual used in a post or the overall brand identity carry more weight in the judgement of authenticity than post captions. Another aspect that needs to be considered, is that no AI-disclosure was given on the posts, as it was not needed. Therefore, no clear indication was provided, which might have prevented observed authenticity violations by users. Overall, the findings suggest that concerns about reduced authenticity through AI-implementation are highly dependent on the context.

Regarding the commitment-trust theory (Morgan & Hunt, 1994), if ACC had threatened users' trust in the brand and, in consequence, weakened their commitment, it should have reduced engagement. Since no decrease was found, it can be assumed that no loss of trust followed from ACC. Because no significant differences in engagement were found between ACC and HCC, the underlying brand relationship appears to have remained stable. This could mean that users' either did not notice that captions were written by AI, or they did not perceive ACC as less trustworthy. In the context of this field setting, this could also mean users' trust in the brand had already been established on a high level before the experiment, which protected it against negative reactions to AI use. In this case, pre-existing commitment likely drove engagement more strongly than the source of the post caption. However, as trust among users was not measured directly, these conclusions cannot be taken as definitive.

Furthermore, the results of the present study add an aspect to how the commitment-trust theory (Morgan & Hunt, 1994) can be interpreted in digital contexts. While the theory assumes that lowered trust causes a decrease in commitment, the present findings did not show a decrease in user engagement for posts with captions produced by AI. This suggests that, in this real social media context, trust was not visibly harmed by ACC, at least not when the use was not openly declared and the brand appearance remained consistent.

Therefore, the present study proposes a nuance to the theory, namely that trust might be tied more strongly to overarching brand aspects, such as brand reputation or visual identity, compared to authorship of post captions on Instagram, in a digital and fast-paced context. The results imply that AI-created content, at least in non-critical contexts of use like social media captions, does not lead to observable reductions in users' engagement that would indicate a breach of users' trust. This suggests that the commitment-trust theory

(Morgan & Hunt, 1994) might require an additional nuance in GenAI-related brand communication contexts.

Research question two additionally deals with the effects of different content types. For informative, promotional and entertaining content no differences in user engagement were found, regardless of whether the captions were written by AI or a human. In line with the uses and gratifications theory by Katz et al. (1973a), user engagement should have decreased, if the gratifications obtained did not match the gratifications sought. Since this did not occur, several explanations are possible. First, it seems that gratifications may be fulfilled across all categories, regardless of the type. Second, engagement likely depended more on factors that were not manipulated, such as the algorithmic exposure or the visual and aesthetic quality. The results additionally showed that content type alone may be insufficient to predict user engagement.

Although the descriptive statistics showed strong differences between content types, they were not significant when the ART ANOVA was calculated. The rather small sample size in each cell of the design and the high variance explain this discrepancy. Especially promotional content showed very large standard deviations, which indicates that engagement varied strongly and inconsistently among posts in this category. This high variability within the group affects the statistical power. Given the small number of posts per group, this study may not have had enough power to detect subtle effects between content types, even though these effects might exist. Therefore, the non-significant results should be interpreted cautiously, since they indicate that no statistical pattern was found, but it is still possible that content types affect user engagement differently, in general and in the context of ACC and HCC, under different conditions or with larger samples.

Even though previous research suggested different effects depending on the content type, this present study did not replicate this pattern. One possible explanation might be that the gratifications connected to informative, promotional or entertaining content might have been fulfilled independently of the category. For example, if, for entertaining content, users relied primarily on the visual and less on the caption, their need for entertainment might have still been satisfied. Informative content might not have gotten shared less, because, on average, the content was interesting and easy to understand.

To the best of knowledge, this study was the first one conducted in a real-life setting on a brand's Instagram account. The results showed that in this context, ACC can be employed without causing harm to engagement, which challenges the assumption that AI reduces trust or perceived authenticity. In contradiction to previous studies, ACC did not perform worse, which may be explained by the fact that users were not asked to consciously evaluate the content. Moreover, user behavior in real-life may differ from lab-based evaluations and Instagram engagement is fast, habitual and low-effort, therefore authorship of post captions, if aligned with the brands tone of voice, might be irrelevant.

Implications for research and practice

The findings of this study show that ACC is not necessarily harmful for behavioral engagement but instead can have strategic relevance for marketers to save time and simultaneously maximize output. Earlier lab-based research that showed lower authenticity, trust, and engagement for ACC is partly challenged by the findings regarding behavioral engagement. In this real-life setting, no lower levels for likes, comments, shares, saves, or views were found. However, since authenticity and trust were not directly measured, no conclusions can be made about these constructs. Additionally, the absence of an AI-disclosure might be a main moderator that was previously overestimated in past research. Therefore, in the future, ACC with and without disclosure should be distinguished. Moreover, as controlled experiments might not capture real user behavior on social media, researchers should combine field experiments with lab studies so that discrepancies can be better understood.

While previous research has shown that caption authorship might strongly affect user reactions, other factors like brand trust, visual quality, audience involvement, or a brands' defined tone of voice may moderate the effect. Moderators and mediators should therefore be tested in the future, instead of only focusing on main effects.

Since the expected differences in content types were not observed, they might be weaker than expected or overshadowed by factors connected to the algorithm or the visuals. Hence, research should revisit whether the definitions of categories are still applicable in the context of AI. Moreover, as AI is constantly gaining relevance in fields such as marketing and communication, Authenticity theories and research in general should integrate AI-mediated communication as a new variable to better understand the effects of its use.

Moving on from implications for research to practice, an evident one is that, according to the results of this study, brands can incorporate AI-generated captions without harming engagement. As no significant evidence of reduced engagement across likes, comments, shares, saves, or views was found, ACC can be adopted for regular content on social media. Nonetheless, AI-generated output should always be reviewed and adapted if needed, as it was also done in this study. Previous research has shown the negative effect of AI-disclosures regarding trust, whereas the new findings did not show significant negative impact. Based on this, a recommendation is to only disclose the use of AI when it is required, for example when using pictures produced by GenAI.

According to the findings of this study, engagement might be only weakly influenced by the text accompanying the post and may be more affected by other aspects such as the visual used, product interest, or algorithmic reach. Therefore, brands should prioritize high-quality visuals and storytelling, with captions serving more as supportive elements for an additional layer of information or entertainment. Additionally, since no significant differences were found in the performance of posts in the defined content type categories, the focus from strict categories should potentially be shifted toward execution quality.

Without negative responses, the use of AI can strongly increase content scalability. As engagement metrics remained consistent throughout this study, GenAI can be used to create content faster and post more frequently. This allows marketers to reallocate resources toward strategy and content planning. Moreover, if captions are regularly composed by AI, clear brand voice prompt guides can be established and shared within a company, to ensure clear and coherent communication without ambiguities.

While, according to the results of this study, GenAI brings relevant benefits for practice, people and brands who incorporate AI in public communication should stay alert. As the public awareness of AI increases, preferences and sensitivities of users might shift. Therefore, it is strongly recommended to track engagement and sentiments in comments over time and be aware of changes.

Limitations and Directions for Future Research

This study encountered several limitations. The most important limitation was the very small sample size, which in turn affected statistical power. With only 21 posts per content source and 14 per content type, statistical power was very low, which made it harder to detect subtle effects in statistical analysis. Because the ART ANOVA and non-parametric tests require larger samples to detect interactions, some descriptive differences may not appear as significant effects due to insufficient power. This is highly relevant, because findings may be correct but not definitive, because, in this study design, small or medium effects cannot be ruled out.

Additionally, the real-life setting of this study limits control. Factors that could not be controlled, like the algorithm or activity patterns of followers, introduced noise, which might have masked the differences between ACC and HCC. Posts with higher engagement metrics and view time compared to the average might have been favored by the algorithm and thus shown to more people. This could have increased user engagement, simply because of a higher presence that ultimately had less to do with the caption and more with the product shown or the photo in general. Likes and comments also depend on the visibility of posts, whereas visibility depends on the algorithmic push.

Another limitation concerns the relative importance of visual content on Instagram. As a highly visual platform, users might base their engagement decisions on the photo or video content, rather than the caption. Since the visual is already in focus, this results in a natural limitation of the influence of post captions, whether AI-generated or written by a human. Therefore, the chosen study design reduced sensitivity for detecting these caption-based effects. Since it was impossible to publish regular posts with identical pictures, where only the captions would change, the isolated effect of ACC cannot be determined in within this study design. Certain visuals might have appealed to a broader audience, compared to others. This could have potentially also affected how the post was treated by the Instagram algorithm. The algorithmic distribution was a further limitation. Since every post is treated differently by the algorithm, affecting visibility, each post was shown to a different group of users, with different engagement habits. Therefore, the engagement metrics not only reflect user engagement and preference but also algorithmic visibility, which could not be standardized in this study.

After the data collection was completed and descriptive statistics were calculated, a high variance in engagement metrics was identified. The extremely high standard deviations were strongly fluctuating, which was potentially caused by algorithmic reach and not by the quality of the caption. While this limits interpretability, it does not invalidate the analysis. This large variance made the statistical detection of differences very difficult.

The used classification for content types might also pose a limitation. While the defined content types, informative, entertaining, and promotional are conceptual categories, a single post might incorporate aspects from several content types. Therefore, the human categorization might not accurately reflect user perceptions.

Another limitation was that all posts written by a human were composed by a single person and not cross-checked or revised by other team members. Although the captions followed the brand's guidelines, the writing style, tone, or creative approach of this person might not fully reflect the broader range of human-authored content. Stylistic tendencies by the individual might affect users' perceptions and engagement with these posts. Therefore, if HCC underperformed in any way, this might partly reflect the writing style and preferences of the author, rather than representing HCC more generally.

Additionally, the study design limits the generalizability of results, as it was only conducted on a single brand, with an industry specific tone and audience. Since audience characteristics also affect user engagement behavior, the findings cannot be directly transferred to other brands, industries, or platforms.

Lastly, since the captions created using AI were reviewed by a human and, if needed, edited once, they cannot be considered s "pure AI output". This may have attenuated the difference between ACC and HCC and therefore, the isolated effect of ACC vs. HCC cannot be determined. This is relevant because unreviewed AI output might change user engagement under different conditions.

This field experiment had a strong explorative aspect. Future research needs to test whether the chosen theories explain user engagement and reaction in this context. Additionally, due to the study design, it is not clear how users perceived the caption or if they even read them. All these limitations raise the need for future research to change the setting and test different aspects. Recommendations and ideas are presented in the next chapter.

Different recommendations arose during the conduct of this study. An obvious one is to increase the sample size and thus extend data collection. By keeping the design as it is but collecting a larger number of posts per content type and content source, statistical power can be increased. It is important to maintain an equal representation of all content types, so that the interaction effects of content source and type can be meaningfully tested. Additionally, a longer observation period avoids time-specific algorithmic fluctuations.

In order to facilitate a more precise analysis of the effect of ACC on user engagement, it would be recommended to conduct a study in which the two compared posts are as similar as possible, to minimize the moderating factors of different visuals. This could be done by making A/B-tests in advertisements on social media, for example though Meta Ads. Here, the identical visual can be used and only the caption changed. This allows for randomized exposure, and while the ads are still shown to different groups of users, they should all belong to the specified target group and be rather similar. This would increase internal validity and also allow a more detailed analysis, since a wider variety of performance and engagement metrics, such as click-through rates or link interactions, can be included. Engagement could also be analyzed as "relative to reach", instead of absolute numbers.

Since AI-output was lightly revised by a human in the present study, future research could include unedited AI-generated output. In this study, unrevised ACC could be compared to lightly edited, heavily edited, and professional output written by a human, to see whether the editing masks differences between ACC and HCC.

A clear finding of previous research was the negative effects of an AI-disclosure on users' and test objects' reactions. This could be further tested in a real-life setting, to test how the labeling of AI affects authenticity, trust, or willingness to engage. This could also be taken a step further, where, instead of post captions, the visual is created by AI. In this case, the AI- disclosure is obligatory, and ACC can be compared to similar pictures produced by a human professional.

As this study was conducted on a niche branch, following studies could integrate more brands or conduct comparisons between different industries. The same study could be conducted with different brands and thus investigate, whether brand strength, audience demographics, or brand tone moderate reactions. In the next steps, it could be tested how these results change depending on which platform the posts are published on. This comparison of industries would shed light on whether user reactions to ACC depend on audience types, platform norms, or content consumption habits. Consequently, boundary conditions of the effectiveness of content created by AI could be identified.

The present study relies solely on behavioral data, thus what users actually notice or thought when they viewed the posts is unknown. By including qualitative methods, user perceptions could be better understood. They could be incorporated as follow-up interviews, to better understand whether users really read the captions, if differences between ACC and HCC were perceived, or how authenticity and trust in the brand were judged. This would help to make the interpretation of engagement data more accurate and potentially link it to psychological constructs.

Conclusion

The purpose of this study was to examine how brand posts with AI-generated captions perform compared to human-written ones in a real-life setting on Instagram. Additionally, different content types were included to investigate whether ACC and HCC would perform differently depending on the content type. Previous research was mainly conducted in lab-based settings or hypothetical scenarios, and field experiments on Instagram were missing from the literature. Additionally, studies often focused on the effects of AI-disclosure. The research gap regarding studies conducted in realistic settings and focusing on the undisclosed use of GenAI was addressed in this present study. To investigate the effects of using ACC, the overarching research question was: How does AI-created content (ACC) affect user engagement compared with human-created content (HCC) on a real brand's Instagram channel? The first research question focused solely on the different outcomes in user engagement between ACC and HCC, while the second one additionally considered how user engagement differs across content types, and whether this variation depends on the content source.

Statistical analysis showed descriptive differences in user engagement between ACC and HCC, but ultimately a Mann-Whitney U-test found no significant differences across any engagement metrics. Based on these results, ACC performed equivalently to HCC in this present study. It is important to emphasize that ACC was allowed to be revised once, if needed, in order to fit the defined tone of voice of the brand. Nonetheless, the final captions were still written by AI and were only given minor corrections in a second prompt. Even though the findings contradict previous ones, ACC did not perform worse than HCC. The posts accompanied by AI-generated captions were not labeled as AI-created, therefore, the negative effects of ACC found in research that investigated the disclosure of AI do not apply here. For research question two, descriptive patterns suggested that informative content led in most metrics. Nonetheless, the ART ANOVA found no significant main or interaction effects. The Kruskal-Wallis test, which was conducted for further explorative research, showed no systematic differences across content types within the two content sources. The conclusion, drawn from these results, is that content type did not influence engagement, and none of the content types interacted with either ACC or HCC.

Interpreted through the uses and gratifications theory by Katz et al. (1973a), the findings suggest that sought gratifications may have been met independent of authorship or the content type. Therefore, authorship and different content types may not matter for gratification in fast-paced social media environments. Referring to the commitment-trust theory by Morgan and Hunt (1994), user engagement should have been lower for ACC, if it had harmed trust. Since no reduction was seen, it can be concluded that ACC did not affect trust, and therefore, the commitment by users remained stable. In contrast to prior studies that indicated lowered perceived authenticity if brands incorporated GenAI in content production, brand posts on Instagram without a disclosure, did not have a negative effect in this study. Similar to the previously stated theories, authenticity might also depend more on post consistency, visuals, or the brand identity than on caption authorship. In conclusion, the overarching research question, as well as the first subordinate one, can be answered as follows: In this study, no evidence was found that indicates that ACC leads to different levels of user engagement than HCC on a real brand's Instagram channel. With regard to the second research question, the descriptive results showed that informative content performed better than entertaining or promotional content in four out of five engagement metrics. Nonetheless, no statistically significant differences were found, neither for the content types, nor between ACC and HCC within each content type.

This study is, to the best of current knowledge, the first one to test the difference between ACC and HCC using engagement metrics from real Instagram posts of a brand. The results of similar engagement between posts with captions from the two sources challenge earlier findings, which reported negative effects of ACC. This shows that brands can incorporate GenAI for writing post captions when a human remains in the loop and high visual quality and tone of voice are maintained. In conclusion, the main research question can be answered by stating that, in this context, ACC does not negatively impact user engagement and can be incorporated into social media communication, as long as brands carefully manage consistency, maintain a high quality and continuously monitor user reactions and engagement. Nonetheless, it is important to reiterate that these conclusions apply to the specific conditions of this study, which consider a trusted niche brand, content with a strong product-focus, no provided AI-disclosure and lightly revised outputs. Under these circumstances, ACC did not perform worse in regard to user engagement, but this might not be generalizable to other brands or industries.

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Appendix

Published Posts

This table includes all posts that were published on the Instagram account of Leica Camera Classics as part of this study.

ACC	Visual	HCC	Visual
Personalizing your Leica is what makes it truly yours. Whether it’s adding a colorful strap, changing the leather or giving your camera a unique touch in some other way - each change reflects you. How do you make your Leica one of a kind? Drop your favorite customizations in the comments below 👇📷 #LeicaCamera #LeicaCameraClassic #analog #filmisnotdead #classiccamera #vintageleica #analogphotography #LeicaMP #summicron50 #summicron		What will be your summer companion this year? ☀️🐚🌊📷 #LeicaClassic #LeicaCamera #LeicaM6 #LeicaCameraClassic #summer #summerphotography	
Sundays are for slowing down. Quiet spaces, thoughtful details - and a camera that sees only in light and shadow. The Leica M10 Monochrom, on a museum stroll. What’s your ideal Sunday with a camera? 📷👇 #LeicaM10Monochrom #MonochromeOnly #MuseumLight #LeicaInTheWild #35mmView		Mornings are better with a Leica M-A in hand ☕🌸 #LeicaCamera #LeicaCameraClassic #summicron #LeicaMA #leicapreowned #preowned #LeicaClassic #analog	

Did you know the Leica IIIg was the last screw-mount Leica?

Introduced in 1957 and produced until 1960, it marked the end of an era before Leica fully transitioned to the M series and other product lines.

Though it shares the DNA of earlier models, the IIIg introduced several thoughtful upgrades:
📷 A bright viewfinder with projected 50mm framelines and 90mm corner markers
📷 Automatic parallax correction, linked to the rangefinder
📷 Split shutter speed dials - T to 1/30s on the front, 1/30 to 1/1000s on top
📷 Flash sync automation with clearly marked sync speeds
📷 Enlarged rangefinder housing with a secondary window for frameline illumination
📷 Diopter correction lever marked with ±
📷 Film reminder dial placed on the back, similar to the M3

These refinements gave the IIIg a quiet, dignified farewell - closing the chapter on Leica screw-mount design.

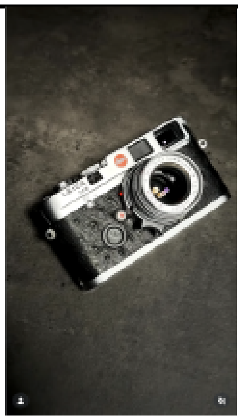
Have you ever photographed with a Leica IIIg? Share your experience below ⬇️📷

#LeicaIIIg #VintageLeica #RangefinderCamera #35mmPhotography #LeicaCamera #LeicaCameraClassic #analog #filmisnotdead #classiccamera

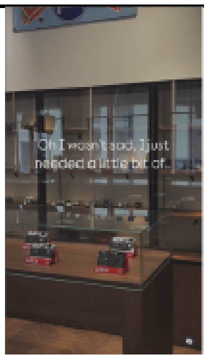
Among the last screw-mount cameras Leica produced was the Leica IIf. While it was practically the same as the IIIf, a noticeable difference was the absence of the slow shutter speed dial on the front of the camera, which was instead covered by a circular vulcanite trim.

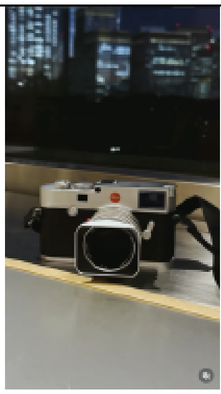
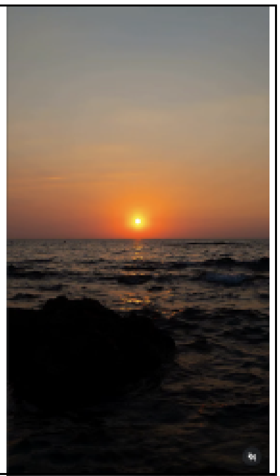
The Leica IIf came with two different flash synchronisation dials. Early versions built in 1951 and 1952 featured a black dial, while models produced from 1952 until 1956 had a red dial. The shutter speed sequences also differed between the two: versions with the black dial had speeds of 1/30, 1/40, 1/60, etc., whereas red dial versions had speeds of 1/25, 1/50, and 1/75. Models produced from 1954 to 1956 additionally featured a shutter speed of 1/1000.

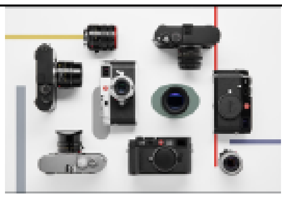
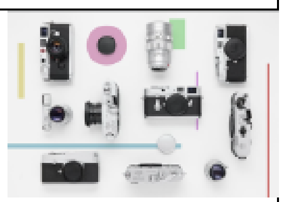
#LeicaCameraClassis #LeicaCamera #LeicaClassic #LeicaIIf

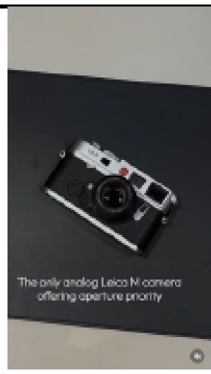
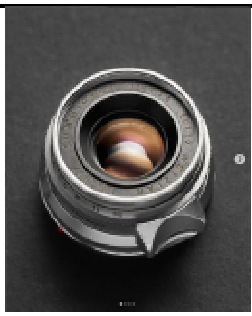
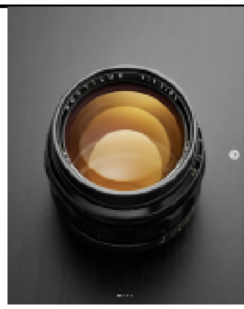
#vintageleica #analogphotography			
Leica M6 ‘Year of the Rooster’ A special chrome edition issued in 1993 in celebration of the Chinese zodiac - produced in just 300 examples and paired with a matching Summicron-M 2/50mm no.240/300. Complete with its original wooden presentation box. This mint-condition set will be available at the 46th @leitz_photographica_auction on June 27, alongside over 440 vintage cameras and accessories 📷✨ Pre-bidding is now open via the link in our bio. Would you add this one to your collection? Let us know below 👇 #LeicaM6 #LeitzAuction #SpecialEditionLeica #LeicaCollectors #VintageLeica		This beautiful camera is the 62nd Leica M1 ever produced! At the upcoming 46th @leitz_photographica_auction bidders will have the opportunity to acquire this Leica M1 with serial number 950062, which was manufactured in 1959 and still features an early button rewind knob. It comes with a feet scale Elmar 2.8/50mm and both camera and lens are near-mint condition. Starting Price: €1,600 🔗Visit the online catalog through the link in our bio and place your bids today 📦📷 #LeitzPhotographicaAuction #LeicaCamera #cameraauction #auction #rareleica #leicacollectible #Leica #LeicaM1	
Two cameras. One digital, one analog. Both grounded in the same design language, yet made for different rhythms. Do you reach for the M6 or the M9? Film or digital - what feels right to you? 📷👇 #LeicaM6 #LeicaM9 #RangefinderCamera #LeicaClassic		28mm vs 50mm The focal length you choose changes your image like nothing else. Many photographers have a “ride or die” focal length they always come back to. Which one is yours? Are you leaning towards a standard lens, a wide-angle or something else?🔍🌇 #LeicaCamera #LeicaCameraClassic #LeicaM6 #LeicaM7 #leicapreowned #preowned #LeicaClassic #analog#50mmPhotography #28mm	

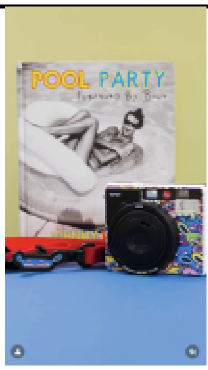
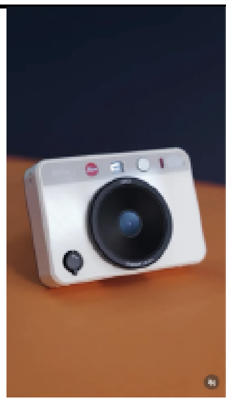
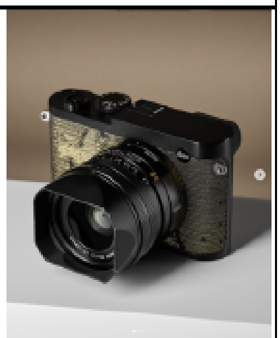
A true classic - up for auction. This late Summilux 1.4/35mm Steel Rim in chrome, originally made for the Leica M2, comes in near-mint condition with very good optics. The set includes a matching OLLUX hood and UVa filter. It will be available at the 46th @leitz_photographica_auction on June 27th, alongside over 440 vintage lots, cameras, and accessories 📷🗓️ Whether you're a collector or simply appreciate rare lenses, this is one not to miss. #Summilux35 #LeicaM2 #LeitzAuction #VintageLeica #LeicaCollectors		Suited for everyone who is looking for something special, this very rare, beautiful early Summilux 1.4/50mm will be available at the upcoming 46th @leitz_photographica_auction on June 27th. This beautiful lens with an original M39 mount is in mint condition, with very good optics and comes together with both caps, UVa, yellow and orange filters, a hood and a beautiful leather case. Bids can be placed in advance in just a few steps, so head over to the website - the link is in our bio.🔗 Happy Bidding!📸 #LeicaCamera #LeicaCameraClassic #Summilux #leicapreowned #preowned #LeicaClassic #analog	
Leica Minilux Zoom (1998–2004) An advanced compact designed for flexibility, featuring a Vario-Elmar 35–70mm f/3.5–6.5 zoom lens, ±2 EV exposure compensation, and self-timer function. Unlike the original Minilux, this version forgoes aperture priority - but gains extended range in a titanium body with clean, purposeful design. Precision, scaled down. #LeicaMiniluxZoom #LeicaCompact #35mmPhotography #LeicaClassic		Ever came across this one - the Leica D-LUX 6 in high gloss finish?✨🖤 In 2013 Leica released a special version of the already existing Leica D-Lux 6 - a glossy Version with a silver lens. Still having the same features as the regular Leica D-Lux 6, the camera came with a fast f1.4-f2.3 lens of 4.7-17.7mm, which is equivalent to a 24-90mm lens. It had manual controls for focus and exposure, including a built-in three-stop ND filter, which made the camera intuitive to operate and gave photographers more creative control. It featured a then new 1/1.7-inch CMOS sensor with 12.7 MP, delivering	

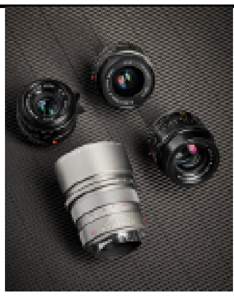
		solid performance in a compact form. #LeicaCamera #LeicaCameraClassic #LeicaDLUX6 #leicapreowned #preowned	
Leica M6J Released in 1994 to mark 40 years since the introduction of the Leica M3, the M6J blends the classic spirit of the original M with modern refinements. Leica produced just 1,640 examples - 40 for each year from 1954 to 1994 - each with a serial number beginning with the year it represents. A quiet tribute to four decades of rangefinder heritage. Have you come across one of these in person? Let us know below ⬇️📷 #LeicaM6J #LeicaAnniversary #VintageLeica #LeicaCollectors #RangefinderCamera		Have you ever wondered what it's like to take pictures with a camera from 1954? This beautiful, early Leica M3 with serial number 700789 has just arrived in our Marketplace and is ready to find a new owner.🤝📷 Have you ever had the chance to photograph with a camera from this year, maybe even one of the early M models? We're curious to know more ⬇️😊 #LeicaCamera #LeicaCameraClassic #LeicaM3 #leicapreowned #preowned #LeicaClassic #analog	
Too many cameras… and somehow still not enough 🎞️📷 Spotted anything you'd add to your shelf? #LeicaClassicStore #VintageLeica #CameraWalk #FilmIsAlive		Always on our mind 💭 #LeicaClassic #LeicaCamera #LeicaCameraClassic #rareLeica #filmisnotdead #analog #preowned	

One camera, one lens - endless ways to see. With the Leica M10-R and a 35mm lens, quiet details and flashes of colour feel just a little easier to catch - no matter where you are. #LeicaM10R #35mmPerspective #EverydayLeica #LeicaInTheWild #RangefinderLight		This is your sign to capture the most beautiful colors during summer sunsets on a Pre-Owned Leica Q2 📸🌅🌊 #LeicaClassic #LeicaCamera #LeicaCameraClassic #sunset #summer #photography #LeicaQ2	
Leica 0-Series Replica This fully working replica is based on the Leica 0-series - an experimental group of prototype cameras that laid the groundwork for the first commercially produced Leica camera, the Leica I. These prototypes are among the most historically significant 35mm cameras in photographic history. Only around 20 were produced, and roughly half remain in existence today. A rare homage to a defining moment in the history of photography. #Leica0Series #LeicaHeritage #LeicaHistory #35mmPhotography #OskarBarnack		The Leica Model B was the second Leica camera introduced to the public, launched in 1926 and produced until 1941. The camera was built in two different versions: the Dial set and the Ring set. Both closely resembled the earlier Model A, but instead of a focal-plane shutter, the „Dial“-version featured a compur interlens shutter with shutter speeds set on a round dial above the lens, while the „Ring“-versions were fitted with a rim-set type shutter, which offered improved usability. The camera was equipped with a 50mm Elmar f/3.5 lens, and supported shutter speeds from 1 second to 1/300 second, along with "Time" and "Bulb" modes. The exposure counter was placed where the shutter speed dial would typically be found. Meanwhile, the standard shutter release button was repurposed as a sprocket release, which had to be pressed after each exposure to release the film transport mechanism. #LeicaCamera #LeicaCameraClassic #Leicab #leicacompur #leicapreowned	

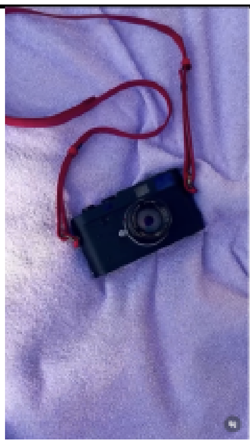
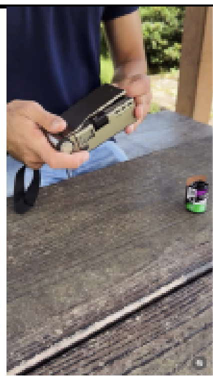
		#preowned #LeicaClassic	
Leica 250 GG Reporter Built for extended shooting, the Leica 250 - internally designated LOOMY - was a rare variant of the Leica III, equipped with enlarged film chambers for ten metres of film, allowing up to 250 exposures per load. Film would pass through the camera from one cassette to another, making it possible to remove partially exposed rolls. A large, engraved film counter beneath the winding knob marked 0–250 stands as one of its most prominent features. This version, known as the 250 GG, was produced from serial no. 150125 with a top shutter speed of 1/1000, matching the Leica IIIa. While official production ended in 1942, 33 more units were assembled through 1953. Ever seen one in person - or had the chance to shoot with one? Tell us below ⬇️📷 #Leica250GG #LeicaReporter #VintageLeica #LeicaHistory #35mmCamera		1839 – 1914 – 1989 This platinum-finish Leica M6 was issued in 1989 to commemorate 150 years of photography and 75 years of Leica photography, marking the revolutionary impact of the Ur-Leica, invented by Oskar Barnack. To honour these turning points, Leica released a limited anniversary edition of the M6, featuring a platinum-plated body, a special leather covering, and a matching platinum-plated Summilux-M 1:1.4/50mm lens. Only 1,250 pieces were produced, each engraved with a letter from the word LEICA. #LeicaCamera #LeicaCameraClassic #LeicaM6 #photography #LeicaM #filmphotography	
From the high-resolution precision you seek to the refined purity of monochrome, each digital Leica M model offers a different experience behind the lens. At Leica Classic, you have the opportunity to explore them all! 📸 Which digital M cameras have you tried so far, and which ones are still on your list?		All analog. All M. From the M3 that started it all in 1954 to the M1, M5, and beyond - each with its own character, its own view of the world. A quiet reminder of how much can be captured without saying a word. #LeicaM #AnalogOnly #VintageLeica #RangefinderLove #35mmFilm	

#LeicaCameraClassic #LeicaCamera #LeicaClassic #LeicaM #leicadigital			
With its release in 2006, Leica made a big step, as it was the first digital camera in the M-System. With around 10 MP and an APS-H CCD sensor, the camera offered a very film-like look with a unique digital 'grain'. Have you ever had the chance to try this camera, and if yes, how do you like its look?📸 #LeicaClassic #LeicaCamera #LeicaM8 #LeicaCameraClassic		Leica M7 (2002) The direct successor to the M6, the M7 introduced a new level of precision to the M system - becoming the first and only model to feature an electronically controlled shutter. It offers both aperture priority and stepless automatic exposure, while preserving the familiar manual metering experience that defines the Leica M. A bridge between tradition and modernity - marking a subtle shift in how the M camera responded to light. Have you worked with the M7 before? We'd love to hear your thoughts below⬇️📷 #LeicaM7 #LeicaM #RangefinderCamera #35mmPhotography #FilmCameraCommunit y	
Leica Summicron-M 35mm f/2 V1 Introduced at Photokina in 1958, this was the first standard wide-angle lens with a fast f/2 aperture - developed by Walter Mandler and produced primarily in Canada. Known among enthusiasts as the "8 elements" Summicron, it features an optical design that renders with subtle softness and exceptional depth - creating images with a distinctly cinematic character. Produced until 1969, it remains one of the most admired M lenses for its		As the first serially produced lens ever to incorporate aspherical elements, the Noctilux 50 f/1.2 was an exceptional step forward in the history of photography.🏛️📷 It was introduced at Photokina in 1966 and made available to the public the same year. With its revolutionary design, incorporating two aspherical elements in the front and rear parts of the lens, it reduced spherical aberration at maximum aperture and thus increased the quality of the image field. In addition, offering a maximum	

classic draw and timeless rendering. Have you experienced this version firsthand? We'd be interested to hear your impressions below ⬇️📷 #Summicron35 #LeicaLensHeritage #WalterMandler #35mmClassic #LeicaHistory		aperture of 1.2, it was a rarity by the standards of the time and offered exceptional optical performance overall.✨ #LeicaCamera #LeicaCameraClassic #Noctilux #LeicaM #leicapreowned #preowned #LeicaClassic #analog	
Leica SOFORT 'LimoLand by Jean Pigozzi' The first-ever special edition of the Leica SOFORT, released in 2017 in collaboration with Franco-Italian photographer and designer Jean Pigozzi. With its bright, playful design and signature Mr. Limo character on both front and back, this version stands out from every angle. It comes complete with a red Artisan&Artist strap in high-quality nylon with leather trim - also featuring the Mr. Limo logo in blue. A standout piece for collectors and anyone drawn to creativity in instant form. Now available - contact us for details. #LeicaSOFORT #LimoLand #JeanPigozzi #LeicaSpecialEdition #InstantPhotography		In an increasingly digital world, the Leica Sofort 2 offers an analog experience, inviting creativity, connection, and tangible results.📸🌅🏞️ A Pre-Owned Leica Sofort 2 has just arrived in the Marketplace - check it out, the link is in our bio🔗 #LeicaCameraClassic #LeicaCamera #LeicaClassic #leicasofort2 #sofortbild #sofortbildkamera #instantcamera	
Leica Q3 (Typ 343) with special leather covering This near mint Q3 stands out at first glance - fitted with the striking leather from the Leica M6 Platin '150 years' edition. Originally created for a special anniversary model, the textured finish gives this camera a distinct look that sets it		Are you looking for something out of the ordinary?📷✨ The Leica Classic Marketplace offers a range of rare collectibles, from strictly limited special editions to vintage photographic equipment.	

apart from the standard version. Same performance, entirely different presence. More details are available on the Leica Classic Marketplace - or feel free to send us a message. #LeicaQ3 #LeicaDesign #LeicaClassicMarketplace #LeicaCraftsmanship #LeicaStyle		Visit the Leica Classic Marketplace today - you can find the link in our bio. #LeicaCameraClassic #LeicaCamera #LeicaClassic #vintage #leicacollectible #collectibles #specialedition	
Understanding Leica Lens Design: APO and ASPH. Each Leica lens is built with a specific optical philosophy. Seen here: a group of Summicron-M lenses featuring two of Leica's most important technologies - APO and ASPH. 🔍 APO (Apochromatic)In conventional lens design, red light tends to focus on a slightly different plane than blue and green - causing chromatic aberration, especially in longer focal lengths. APO lenses use specialized low-dispersion glass to align all colours on the same focal plane, resulting in exceptionally sharp images without colour fringing. 🔍 ASPH. (Aspherical)Where spherical lens elements have a constant curvature, ASPH. lenses incorporate at least one element with a non-uniform radius. This allows for advanced optical correction in a more compact build - achieving greater sharpness from centre to		In 2001, Leica introduced a new tradition with the release of the special edition Leica M6 TTL ‚Titanium'. Since then, cameras with a beautiful titanium finish have been produced from time to time, always as strictly limited editions. Whether it's an M camera or a Leica Q in titanium, these pieces stand out for their eye-catching look. To complement them, various matching lenses were manufactured in this beautifully refined, particularly resilient, and hardwearing material, completing the setup with subtle elegance. 📷✨ #LeicaCameraClassic #LeicaCamera #LeicaClassic #LeicaPreOwned #titanium #collectible	

edge without increasing the size of the lens. Each approach brings technical refinement to optical performance - at the service of clarity, precision, and rendering quality. #LeicaLenses #LeicaASPH #LeicaAPO #SummicronM #LeicaOptics #35mmPhotography			
Leica MP 'Republic of China Centennial' Edition Released in 2012 to commemorate 100 years since the founding of the Republic of China, this limited edition Leica MP is one of just 100 examples produced worldwide. Finished in M2-inspired grey and engraved with a gold plum blossom motif, the camera is paired with a matching Summilux-M 1.4/35mm ASPH. lens. This set comes complete with original accessories, papers, and maker's box - and is offered in like new condition. Now available on the Leica Classic Marketplace. You'll find the link in our bio. Have you come across this edition before, or is this your first time seeing it? 📷👇 #LeicaMP #LeicaSpecialEdition #LeicaCollectors #RepublicOfChinaCentennial #LeicaClassicMarketplace		Just arrived - this beautiful Leica MP Anthracite is now available on the Leica Classic Marketplace. This special edition, limited to just 600 pieces, was produced to commemorate 50 years of Leica M photography. 📷 The camera comes together with a matching Summicron-M 2/35 ASPH., one of only 400 produced, and a Leicavit for fast shooting. Click the link in our bio and have a look at this exceptional camera ✨ #LeicaClassic #LeicaCamera #LeicaCameraClassic #LeicaMP #rareleica	

Leica Classic Marketplace Where rarities meet the right hands. From a Leica M6 Ein Stück Leica to a Leica IIIf Black Dial “Dummy”, the Leica Classic Marketplace features a curated selection of special pieces - not always easy to find, but carefully sourced and presented. Explore a changing collection of vintage and pre-owned cameras, lenses, and accessories - all available online. 📍 Link in bio. #LeicaClassicMarketplace #LeicaCollectibles #VintageLeica #LeicaM6 #LeicaIIIf #LeicaCameras		Explore Leica Vintage in our Marketplace 🔍 We always offer a curated selection of special editions, Leica screw-mount cameras, vintage lenses and so much more so click the link in our bio and find the next piece to add to your collection. ✨ #LeicaClassic #LeicaCamera #LeicaCameraClassic #vintage #preowned #filmphotography #filmisnotdead #leicascrewmount #LeicaM6	
Long shadows, soft light, and colours that linger just a little longer. There’s something about summer that slows everything down - just enough to notice. How does the season change the way you see or photograph? ☀️📷 #SummerLight #LeicaClassic #SeasonalStories #LeicaCamera		Nothing beats the satisfaction of loading a new roll and getting ready for new adventures 🤝📸 #LeicaClassic #LeicaCamera #LeicaCameraClassic #minilux #analog #filmisnotdead	

Use of AI tools

This table lists all AI tools that were used for different parts of this thesis.

AI based tool	Form of use	Parts of the work concerned
DeepL	Translation of words/passages. Finding synonyms.	Whole thesis
ChatGPT-4o / ChatGPT-5.1	Structuring chapters. Proofreading the thesis for grammatical errors. Feedback on scientific structure and argumentation.	Whole thesis
ChatGPT-4o	Reformulate the hypotheses as conditional sentences.	Chapter “Research Questions and Hypotheses”
ChatGPT-5.1	Problem-solving during statistical calculations.	Chapter “Results”

Abstract

German

Die rasante Entwicklung der Künstlichen Intelligenz (KI) hat die zentralen Prozesse des digitalen Marketings, insbesondere der Erstellung von Inhalten für Social Media, fundamental verändert. Während Unternehmen zunehmend mehr KI-generierte Inhalte in ihre Kommunikationsstrategien einfließen lassen, stellt sich die Frage, wie Konsumentinnen und Konsumenten auf diese Inhalte reagieren. Obwohl bereits einige Studien die Wahrnehmung von KI-generierten Inhalten untersuchten, wurden diese Experimente in kontrollierten, experimentellen oder nicht realitätsnahen Online-Settings durchgeführt. Untersuchungen in einem realen Setting wurden dabei weitgehend vernachlässigt. Die Erkenntnisse sind oft gemischt, vor allem in Bezug auf Authentizität, Offenlegung von KI-Nutzung und stilistische Aspekte. Daher sind empirische Beweise für die mögliche unterschiedliche Performance von KI-generierten Inhalten und jenen, die von einem Menschen erzeugt wurden, im realen Kontext auf social media stark begrenzt.

Basierend auf dem Nutzen- und Belohnungsansatz (Uses & Gratifications theory) von Katz et al. (1973), der Commitment-Trust Theorie von Morgan und Hunt (1994) und dem Konzept der (Marken-)Authentizität, untersucht diese Studie die Unterschiede zwischen zwei Inhaltsquellen und drei Inhaltstypen in Bezug auf messbare Engagement Metriken auf Instagram. Diese theoretischen Grundlagen betonen, dass Engagement von funktionalen, hedonistischen und authentizitätsbezogenen Bedürfnissen beeinflusst wird. Darüber hinaus sind das wahrgenommene Vertrauen, Kontinuität und wahrgenommene Aufrichtigkeit wichtige Bestandteile von starken Beziehungen zwischen Marken und Konsumentinnen und Konsumenten. Bisherige Literatur betont außerdem, dass Veränderungen im Ton, Emotionalität und sprachliche Merkmale von Social-Media-Beiträgen die wahrgenommene Authentizität und dadurch das Nutzer Engagement beeinflussen können. Um die Lücken der bisherigen Forschung zu füllen, wurde die folgende übergeordnete Forschungsfrage untersucht: Wie wirkt sich KI-generierter Content (ACC) im Vergleich zu von Menschen erstelltem Content (HCC) auf das Nutzerengagement auf dem Instagram-Kanal einer realen Marke aus?

Um diese Fragen zu beantworten, wurden 42 Instagram-Beiträge auf dem Instagram Account von Leica Camera Classics, im Zeitraum von Mitte Mai bis Ende September, veröffentlicht. Gesamt wurden die Bildunterschriften für die Hälfte dieser Posts von ChatGPT4-o verfasst, während die restlichen 21 Texte von der in der Firma zuständigen Person geschrieben wurden. Die Beiträge wurden in drei Inhaltstypen (informativ,

unterhaltsam und werbend) eingeteilt. Das Nutzer-Engagement wurde anhand von „Gefällt mir“-Angaben, Kommentaren, der Anzahl der geteilten Beiträge, der gespeicherten Beiträge und der Aufrufe gemessen. Deskriptive Statistiken sowie Mann-Whitney U Tests and Kruskal-Wallis Tests wurden berechnet, um das Engagement zu vergleichen. Weiters wurde eine Textanalyse der Bildunterschriften durchgeführt, um weitere Unterschiede zwischen den Texten der beiden Inhaltsquellen zu analysieren.

Die Ergebnisse zeigten keine signifikanten Unterschiede im Nutzer Engagement zwischen KI-generierten und von Menschen produzierten Inhalten. Obwohl Beiträge mit KI-generierten Bildunterschriften in den deskriptiven Statistiken teilweise leicht höhere Werte erzielten, waren diese Unterschiede nicht signifikant. Auch zwischen den verschiedenen Typen der Inhalte wurden keine Unterschiede festgestellt. Nichtsdestotrotz zeigten informative Inhalte höhere Werte in der deskriptiven Statistik. Die Textanalyse zeigte, dass Fragen öfter in KI-generierten Bildunterschriften vorkamen, allerdings führten diese Unterschiede nicht zu systematischen Veränderungen im Nutzerverhalten.

Zusammengefasst zeigen diese Ergebnisse, dass das messbare Verhalten von Beiträgen mit KI-generierten Bildunterschriften vergleichbar mit jenem gegenüber Beiträgen ist, deren Bildunterschriften von Menschen verfasst wurden, sofern Nutzerinnen und Nutzer die Quelle der Bildunterschriften nicht kennen. Das widerspricht der Annahme, dass KI-generierte Inhalte zu geringerem Nutzer Engagement führen und betont stattdessen, dass der Kontext, beispielsweise das Bild oder Video des Beitrags, oder die Qualität des gesamten Beitrags eine entscheidende Rolle bei der Gestaltung der Reaktionen der Nutzerinnen und Nutzer spielt.

Aus betriebswirtschaftlicher Sicht bedeutet das, dass KI in die Prozesse der Erstellung von Bildunterschriften für social media eingesetzt werden kann, ohne sofortige negative Auswirkungen. Wichtig ist dabei aber, den Output der KI von einem Menschen prüfen zu lassen, um sicher zu stellen, dass er den von Unternehmen definierten Vorgaben entspricht. Diese Studie leistet einen Beitrag zur bestehenden Literatur, indem sie Einblicke aus einem realen Marketingumfeld liefert. Weiters wird die Relevanz von zukünftiger Forschung betont, um Nutzerreaktionen langfristig zu untersuchen, sowie die Rolle der Markierung von KI und plattform-spezifische Unterschiede zu beleuchten.

English

The rapid development in the field of AI changes central processes of digital marketing particularly the creation of content. While companies increasingly integrate AI into their communicational strategies, the reactions of users remain unclear. Previous studies delivered mixed results especially regarding authenticity, disclosure of AI use and stylistic differences. Additionally, they have been conducted in controlled or experimental settings. Findings from realistic social media settings are lacking.

Based on Uses & Gratifications theory by Katz et al. (1973), the Commitment-Trust theory by Morgan und Hunt (1994) and brand authenticity, this study investigates the differences in user engagement between AI-created content (ACC) and human-created content (HCC) and different content types. According to these theoretical foundations, engagement is characterized by functional, hedonistic, and authenticity-related needs and trust, continuity and perceived sincerity are central parts of stable brand-consumer relationships. Previous studies showed that differences in tone as well as emotional elements can affect perceived authenticity and thus user engagement. This leads to the overarching research question: How does AI-created content (ACC) affect user engagement compared with human-created content (HCC) on a real brand's Instagram channel?

To answer these research questions, 42 posts were published on the brand account on Instagram of Leica Camera Classics. Half of the posts were accompanied by captions written by ChatGPT4-o, the other half by ones written by the person in charge of social media at the company. The posts were additionally divided into three content type categories (informative, promotional, entertaining). User engagement was measured by likes, comments, shares, saves, and views, which were collected via Instagram Insights. To analyze the data, descriptive statistics as well as a Mann-Whitney u test and a Kruskal-Wallis test were calculated. Additionally, a textual analysis of the captions was conducted. The results showed no significant differences in user engagement between both content sources. Even though ACC showed slightly higher values for some metrics in descriptive statistics, the results were not significant. Different content types also showed no significant differences, but entertaining content had a tendency to perform better. The textual analysis revealed that ACC incorporated more questions, which ultimately did not affect user engagement systematically.

In summary, these results emphasize that ACC can perform similarly to HCC on social media, given that there is no AI-disclosure provided, which contradicts the assumption that ACC negatively affects user engagement. Additionally, they highlight the importance of contextual factors like the image or video used in the post or the overall quality of the post.

From a managerial perspective, it can be concluded that AI can be integrated into the creation of captions for social media posts, as long as the output is checked by a human and aligns with brand guidelines. The study broadens existing literature through these insights from a real marketing perspective and emphasizes the relevance of further research to examine the long-term user reactions, the role of AI-disclosure and platform-specific differences.