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Social Media Data Analysis: Engagement & Personalization Depending on Interest

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ABSTRACT

Over the past two decades, social media platforms have significantly transformed communication, entertainment, and marketing. This paper explores the pivotal role of social media data analysis in digital marketing, focusing particularly on user engagement metrics and advertisement personalization. With billions of users actively producing content and interacting online, platforms like Facebook, Instagram, TikTok, and YouTube have become critical environments for gathering and analyzing user data. Businesses now utilize a variety of analytical techniques, like data mining, machine learning, natural language processing (NLP), and social network analysis (SNA), to understand consumer behavior and tailor content accordingly. This data-driven personalization allows for more effective and relevant ad targeting, boosting user engagement and conversion rates.

Key engagement metrics such as engagement rate, click-through rate (CTR), and conversion rate (CR) are used to measure campaign effectiveness. Furthermore, personalized ad delivery is achieved through demographic, behavioral, interest-based, and retargeting methods, supported by algorithms like collaborative filtering and reinforcement learning. Mathematical models including linear regression, K-means clustering, and Markov chains are also explored to understand and predict user behavior. This study highlights how analyzing social media data enhances marketing strategies, optimizes ad performance, and fosters deeper user-brand connections, ultimately transforming digital marketing into a more interactive and data-oriented discipline.

Key words: Social media analytics**,** behavioral targeting**,** data personalization**,** machine learning**,** click-through rate (CTR), conversion rate (CR), Markov chain modeling

1. Introduction

Over the past twenty years, social media platforms have had a huge impact on how people seem to communicate, share content, and interact online. With billions of users across the globe, platforms like Facebook, Instagram, Twitter, TikTok, and YouTube have become almost necessary for modern communication, entertainment, and information sharing. Although the impact seems to be of great importance for entertainment and communication, it is equally affecting business fields, the most known being digital marketing, where businesses now use social media and data analytics to personalize their marketing strategies and create content that targets specific people, based on their needs.

Analyzing data from social media is essential for understanding user preferences, behaviors, and interaction trends. By gathering large volumes of user-generated content, these platforms can create personalized experiences and serve ads that are more relevant to individual users. This level of personalization has transformed advertising, making it both more impactful, more efficient and more user oriented.

This type of analysis combines techniques from data science, machine learning, and statistics. These approaches can help digital marketing experts gain critical insights into their audience, while monitoring how content is delivered, and finally updating the effectiveness of their campaigns. In this paper, the importance of analyzing social media data will be examined, while it will be focused especially on user engagement metrics and the customization of ads. The mathematical models commonly used in these analyses to offer a clearer view of the engagement techniques, will also be examined.

2. Social Media Data Analysis

Gathering and analyzing data from social media platforms is now a key part of understanding how people engage with content and how businesses can adapt their strategies to boost interaction and sales. This type of analysis offers insights that help brands make smarter and strategic decisions, enhance user experience, and improve the effectiveness of their marketing campaigns. The goal is to always achieve higher percentages in terms of sales, while understanding the clients and their needs and making a better buying experience (Haven, Bernoff & Glass, 2007).

Different Types of Data Collected on Social Media

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

Social media platforms collect a broad range of user data, which can be broken down into different but interconnected categories. That usually happens because of the large number of users engaging with platforms every day, either be uploading data, accepting terms, visiting profiles, downloading or saving images etc. Businesswise, it is of great importance to understand the different types of data that is used every day on social media, so to analyze them correctly and eventually come to the right conclusion, about how can they be used and into what outcome can they lead. While different works suggest different kinds of categories, in this chapter will be presented the most commonly referred (Pelau, Stanescu & Serban, 2019).

One of the most known types of data collected on social media is user interactions and engagement. This usually refers to user actions, for example likes, shares, comments, and/or reactions. These metrics give a clear sense of how users feel about certain content and directly influence how visible or popular that content is. Highly engaged posts can go viral, while low engagement may indicate that the content does not fulfil most people's preferences. In this stage it is important to be said, that not always the "technically best" content goes viral, while there are cases of videos and/or pictures, audios etc. that go viral based on negativity comments and dislikes. However, all those indicators (both likes and dislikes, comments and shares) are especially helpful for evaluating an ad campaign success, spotting trends, and understanding audience behavior. For example, in Facebook platform, posts with more reactions and comments were more likely to appear in users' feeds. Instagram and Twitter also seem to prioritize content based on engagement, which affects how widely content spreads organically. Tik Tok also seems to value engagement but is more focused on shares and reposts rather than likes and comments, while introducing a system that gives points to the creator based on the engagement type (ex: shares give 4 points while likes only 1) (Ho, Clarke & Dougherty, 2015).

A second type of social media data is demographic information. This category includes user details such as age, gender, location, education level, and employment status. Platforms usually collect this via user profiles or activity. Understanding demographic data helps digital marketing experts target their messages more effectively. In marketing terms this is usually referred as segmentation, a process where the experts strategically target their audience based on their needs. For instance, ads for high-end cars may be aimed at adults aged 30–50 in urban areas or with higher status jobs, while fitness promotions might focus on younger, health conscious and fitness related users. One example here could be Instagram ad promotions. Instagram (now Meta) offers demographic targeting tools that can help advertisers reach users based on their age, income and location to maximize relevance and notify them with the most compatible ads with them (Efthymiou & Antoniou, 2012, Ho, Clarke & Dougherty, 2015).

A very important category is also behavioral data. The so called "behavior" is most of the times even more important than demographics category, since it can provide the advertisers of better

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

insights of the users (and hence costumers) needs. Although this category can be sometimes confused with engagement, it is very important to understand the difference. In this category it is tracked what the users like, who they follow, and what they watch. Platforms usually monitor clicks, time spent, login frequency, and more to create detailed user profiles. Experts use this to predict future behavior and deliver more relevant ads. Platforms like tik Tok usually also reward users that interact with the platform the most, by giving them more views and engagement. A great example here is YouTube. Generally, E-commerce platforms study browsing history to suggest products based on past activity. Similarly, YouTube recommends videos based on what users have previously watched (Efthymiou & Antoniou, 2012, Ho, Clarke & Dougherty, 2015).

Next category, and one that is not very much known, is sentiment and textual analysis. Sentiment analysis helps decode emotions in user-generated content. Twitter, for example, serves as a real-time outlet for opinions. By applying Natural Language Processing (NLP), companies can determine whether content reflects positive, negative, or neutral sentiment. When Apple launched the iPhone 12 for example, it used Twitter sentiment analysis to understand how the public reacted and adjusted its marketing accordingly (Efthymiou & Antoniou, 2012, Ho, Clarke & Dougherty, 2015).

Last category is contextual data. This category includes environmental or situational data, such as device type, time of day, and geographic location. These elements help businesses serve content that's not only relevant to user interests but also suited to their current context. A usual example for this is that a travel ad might generally perform better when shown to someone at an airport or browsing flights during the summer holiday season (Leech & Onwuegbuzie, 2007, Efthymiou & Antoniou, 2012).

Tools and Methods for Data Analysis

Given the sheer amount of data created and recycled on social media, companies use specialized tools to better understand their use and uncover meaningful insights. As previously said, the main focus of either a marketing campaign or a business it to provide the user (or costumer) with the content they are most combatable with, eventually helping them to increase sales. It is also important to be said that, while a business goal is to sell more or achieve a better total outcome, it is also to understand the costumer and provide him/her with the best service . That being said, the most common techniques that can be used to analyze data are data mining, machine learning, NLP and SNA (Gambetti & Graffigna, 2010).

The term data mining refers to uncovering different patterns in large datasets. Techniques that are used in this process include clustering, classification, regression, and association rules. These help businesses detect trends, forecast behavior, and refine their strategies. For example, a fitness

ISSN: 2455-8834
Volume:10, Issue:09 "September 2025"

brand might use clustering to group users who frequently engage with workout content and target them with similar ads (Gambetti & Graffigna, 2010).

Machine learning and predictive modeling can be said to be a method that uses past data to predict future behavior. In this case, models (AI, Bots etc.) are trained with different methods on very large and heavy, in terms of data, datasets, to estimate which users will click an ad, buy a product, or engage with a specific content. This includes both supervised (e.g., decision trees) and unsupervised learning (e.g., k-means clustering). For example, Netflix's recommendation system uses filtering to suggest content that similar users have enjoyed. In this case, Netflix suggest movies or series to a specific user, based on similar behavior by likewise users in the past (Ghani *et al.*, 2019a).

Recent investigations emphasize the strategic value of combining Big Data and Artificial Intelligence for evaluating and supporting startups. For instance, Davalas (2020) explores how AI-powered big data tools can track potential customers, refine decision-making, and enhance operational assistance in startup ecosystems. This perspective complements our analysis of personalization and engagement in social media contexts, underscoring that data-driven AI applications consistently provide insights and value across distinct domains.

The NLP refers to natural language processing. A key part of AI, NLP helps analyze and understand written language. It's widely used in sentiment analysis, topic modeling, and content classification. Social platforms use NLP to make sense of user comments, posts, and reviews. For example, Twitter's algorithm categorizes tweets as positive, negative, or neutral, giving brands real-time sentiment tracking (Leech & Onwuegbuzie, 2007b).

Lastly the SNA refers to Social Network Analysis. This tool mostly focuses on relationships between users. SNA is used to find key influencers, trace how information spreads, and map out online communities. For example, during a viral campaign, a brand might identify users whose posts are getting a lot of engagement and work with them to extend the campaign's reach (Leech & Onwuegbuzie, 2007b, Ghani et al., 2019).

3. Engagement Analysis

Engagement is widely recognized as one of the most important indicators of success in digital marketing. As mentioned before, it is also considered as one of the main categories of data collection through social media. Generally, posts with high engagement can indicate that users show interest in a specific post and that interaction is encouraged. However, engagement should not always be connected purely with performance. It is also a strategic tool that helps businesses and marketing experts change or customize their approach, based on users' needs, finally leading their business to build a stronger connection with their customers (Barklamb *et al.*, 2020).

Understanding Social Media Engagement

Social media engagement, as briefly mentioned before, usually refers to how users interact with content on different platforms. The interaction may refer to a huge range of reactions, like shares, follows, clicks, or just passive behavior like simply viewing a post or spending time on a page. While there are different categories of engagement, depending on the paper and classification method, three are the most common to date (Alvarez-Milán *et al.*, 2018).

The first one, being active engagement, includes visible and easy to form interactions, for example likes, comments, shares, and reactions. These actions require direct user involvement and are considered highly valuable since they reflect interest and emotional investment to a post (Perreault & Mosconi, 2019).

The second one is usually referred to as passive engagement. The term passive engagement refers to more subtle interactions, as opposed to the first case of active engagement, that requires time from the user but are not so easily visible or measured. These can be the time spent watching a video, scrolling through content, reading a post from a specific amount of time without directly engaging etc. Although harder to measure, passive engagement still reveals a lot about how users consume content, especially on platforms with videos posting, like Tik Tok (Perreault & Mosconi, 2019 Haven, Bernoff & Glass, 2007).

The third one is engagement depth. This refers to how much time users spend while interacting with content. For instance, watching a video from the beginning to the end shows a deeper level of interest compared to quickly skipping past through it (Perreault & Mosconi, 2019).

Key Engagement Metrics in Digital Marketing

In the previous chapters, the main theory of engagement and interactions was extensively discussed. In this chapter, it will be discussed how different algorithms and key metrics are used in order for specialists to understand how well a campaign is performing (Perreault & Mosconi, 2019).

The first metric is referred to as engagement rate. Engagement rate calculates how many users interacted with a post compared to how many people saw it. It helps determine how effectively the content fits with the audience. The formula used in this case is:

- $Engagment\ Rate = (Total\ Engagment\ \div\ Total\ Followers) \times 100$

The total engagement is the sum of all interactions (shares, comments, reactions). For example, a post with 1,000 likes, 200 comments, and 300 shares viewed by 50,000 users would have an engagement rate of: Engagment Rate= (1500/50000) *100= 3% (Shultz, 2007).

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

A second very important and normally used metric is click through rate (CTR). CTR measures how often users click on a link, ad, or call-to-action button. It's especially useful for evaluating the effectiveness of paid ads. The formula used in this case is:

- $CTR = (Total\ Clicks\ \div\ Total\ Impressions) \times 100$

For example, if an ad receives 500 clicks from 10,000 views, its CTR is 5% (Yang & Zhai, 2022).

Last but not least is convention rate (CR). This metric is used when it is needed to calculate how many users complete a desired action, like making a purchase or signing up, short after engaging with content. The formula for convention rate is:

- $CR = (Total\ Attributed\ Conversions\ \div\ Total\ Clicks\ or\ Visits) \times 100$

For example, if 100 out of 5,000 visitors buy a product, the conversion rate is (100/5000)×100=2% (Deng *et al.*, 2019).

4. Personalization of Advertisements

Personalization is a term that mostly refers to ads and how compatible are they with the preferences of the user. By analyzing user data, platforms can serve ads that are related to each user's habits, interests, and context. This makes ads feel more relevant and increases the chances of engagement and conversion, benefiting both businesses and users (Chandra *et al.*, 2022).

How Ad Personalization Works

Ad personalization uses a variety of user data to ensure that the content shown is compatible with the individual's preferences. This results in highly targeted campaigns that reach the right people at the right time. Even though there are different kinds of targeting the right audience, this chapter will analyze demographic, behavioral, interest-based targeting and dynamic retargeting (Chandra *et al.*, 2022).

The demographic targeting involves categorizing users by age, gender, location, income, and education. It allows advertisers to show different ads to different groups based on who they are.

- Age: Products like retirement plans target older adults, while toys or school supplies may target younger demographics.

- Gender: Ads might differ by gender, for example, cosmetics for women or electronics for men, though approaches are increasingly more inclusive.

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

- Location: Businesses can target users in specific cities or neighborhoods. For instance, a local restaurant may target ads to people nearby.
- Income & Education: High-end products often target users in higher income brackets, while educational services may focus on users with specific academic backgrounds (Chandra *et al.*, 2022).

Behavioral targeting is based on users' past actions, such as:

- Content Interactions: Someone who regularly engages with fashion content is likely to see clothing ads.
- Search History: A user frequently searching for travel destinations might be shown ads for flights or hotels.
- Purchase History: Platforms use pixel tracking to learn what users buy and suggest similar products (Shultz, 2007).

Interest based targeting analyze what users follow, like, and engage with to identify their broader interests. A common example is, as mentioned in a previous chapter: A person who frequently watches fitness content may be shown ads for sports gear, gym memberships, or wellness supplements (Abdel Monem, 2021).

Retargeting shows ads to users who visited a site but didn't complete an action (like making a purchase). Dynamic retargeting goes further by showing specific products the user viewed. For example, if you browse a pair of shoes but don't buy them, you might later see an ad for those exact shoes and sometimes even with a discount (Abdel Monem, 2021).

Ads and Algorithms

Behind every personalized ad is a set of different, well-adjusted algorithms working in order to match the content posted online, with the right users. These models improve over time as they learn from user behavior. Even though there are very different types of algorithms that can be used in terms of ad personalization, few of them are being referred in this chapter (Gambetti & Graffigna, 2010b).

The collaborative filtering recommends content based on what similar users or users with equal interests have liked. For example, if one person watches often sci-fi movies on Netflix, it is highly likely that sci-fi movies that other users have liked, will be recommended. Additionally, content based filtering, focuses on the characteristics of the items that somebody has previously interacted with. For instance, if somebody often like skincare posts, the algorithm will suggest

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

similar beauty products. Lastly, reinforcement learning refers to a technique that adjusts how and when ads are shown based on user feedback. For example, if somebody clicks on an ad and engage positively, the algorithm learns to show that ad, or similar ones, to more people with similar interests (Ho, Clarke & Dougherty, 2015b).

5. Mathematical Models and Equations in Data Analysis

In this chapter, the use of mathematical tools will be examined, in order to give the experts a better insight, especially in terms of large datasets. These algorithms and models can be used in order to predict user behavior, improve content targeting and customize advertisements (Zimmer *et al.*, 2019)

Widely Used Algorithms and Models

A number of mathematical models are commonly applied in the context of social media analysis. They help experts understand user trends, group audiences, and the level of success of a marketing performance (Ghani *et al.*, 2019b).

Linear regression is a statistical tool used to understand how a dependent variable (like user engagement) is influenced by one or more independent variables (such as time of posting, content type, or follower count). It helps predict how different factors impact metrics like likes, shares, or comments. If for example, a brand might use linear regression to estimate how many likes a post will get based on when it's published and who it's targeting (Sykes, 2017).

- Linear regression: $Y = \beta 0+\beta 1*X1+\beta 2*X2+\cdots+\beta n*Xn+\epsilon$

Where:

- Y is the predicted value (e.g., likes),
- X1,X2,...,XnX1,X2,...,Xn are input features,
- $\beta 0$ is the intercept
- $\epsilon\epsilon$ is the error term

Clustering groups users or data points based on similarities. In social media, this helps divide audiences into segments with similar interests or behaviors. For example, a company might use K-Means clustering to group users into categories like sports fans, tech enthusiasts, or fashion lovers, making it easier to send them tailored ads (Hamerly & Elkan, 2015).

- K-Means: Minimize$\sum$i=1n$\sum$k=1Krik$\|$xi−μk$\|$2

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

Where:

- n is the number of data points,
- K is the number of clusters,
- rik indicates if data point ii belongs to cluster k,
- xi is the data point,
- µk is the cluster center.

Markov chains model is a commonly used model where each next step depends only on the current state. In marketing, they're used to track user behavior flows, like moving from ad views to purchases. For example, a Markov model might estimate the chances a user will go from clicking an ad to exploring a product page and eventually completing a purchase.

- Markov chains example**:** P = (0.40.60.30.7)

Where rows represent current states and columns indicate the probabilities of transitioning to the next state (Vasek, 2011).

6. Results

Engagement Metric Analysis

As mentioned before, there are specific metrics and equations, used in order to evaluate how well social media content performs. Three of them, as mentioned in chapter 3, are engagement rate, click through rate and conversion rate. These are shown in **Table 1** below, with examples:

Table 1. Engagment metric analysis

Metric	Formula	Example Calculation	Interpretation
Engagement Rate (ER)	(Total Engagement ÷ Total Followers) × 100	(1,500 ÷ 50,000) × 100 = **3%**	Indicates how much of an audience interacts with content.
Click-Through Rate (CTR)	(Total Clicks ÷ Total Impressions) × 100	(500 ÷ 10,000) × 100 = **5%**	Measures how effective content is at encouraging clicks.

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

Conversion Rate (CR)	(Conversions ÷ Clicks or Visits) × 100	(100 ÷ 5,000) × 100 = **2%**	Reflects success at prompting desired actions post engagement.

These metrics help companies fine-tune their content and strategy. For example, a higher CTR may indicate that the ad is compelling and relevant, while a lower CR might signal issues with landing pages or product appeal (Yang & Zhai, 2022).

Engagement Type Comparison

Even though there are different types of engagement, there are three main categories that can be used to compare engagement. Those are active, passive and depth engagement and their use is presented in table 2.

Table 2. Engagement type comparison

Engagement Type	Description	Value in Marketing	Platform Example
Active	Likes, comments, shares	Indicates direct interest and emotional connection	Facebook, Instagram
Passive	Views, scrolls, time spent	Reflects content consumption habits without interaction	TikTok, YouTube
Engagement Depth	How long users interact with content	Shows commitment to content (e.g., full video view vs. short scroll)	YouTube (watch duration), TikTok

Understanding these types allows businesses to better understand and improve their strategies, using engagement insights for campaigns, and active engagement data to understand and influence interactions (Chandra *et al.*, 2022).

Advertisement Personalization Techniques

Using user generated data, businesses personalize ads to fit consumer profiles. The most effective

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

targeting methods are summarized in table 3.

Table 3. Advertisement personalization techniques

Method	Basis	Application
Demographic Targeting	Age, gender, location	Ads for retirement plans to seniors, or local offers based on city
Behavioral Targeting	Browsing and purchase history	Showing travel ads to users searching for flights
Interest-Based Targeting	Content likes and follows	Displaying sports ads to fitness content consumers
Dynamic Retargeting	Past site visits without conversions	Showing the same product with a discount to non-converting visitors

The combination of these techniques allows businesses to achieve higher engagement and conversion while offering relevant content to users (Alvarez-Milán *et al.*, 2018).

Mathematical Models in Social Media Analytics

To further support marketing decisions, as mentioned in chapter 5, mathematical models are applied. The most used are linear regression, k-means and Markov chains. Linear regression helps predict outcomes such as the number of likes or shares based on content type, time of posting, and follower size. For example**,** in the linear regression case, predicting likes based on follower count and time of posting looks like this:

- Likes = 50 + 0.2*(followers) + 1.5*(time factor) + error

In the case of K-Means clustering**,** the algorithm groups users by shared behaviors or interests for targeted advertising (Hamerly & Elkan, 2017). The grouping is formed in clusters and have the following pattern:

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

Table 4. Using K-means for clustering

Cluster	Interest	Suggested Ad Type
Cluster 1	Tech Enthusiasts	Gadget and software ads
Cluster 2	Fitness Users	Gym equipment, health foods
Cluster 3	Travelers	Hotel, airline, tourism deals

Markov Chains equations **t**rack user behavior flow (e.g., from ad view → product page→ checkout). Transition probabilities can help understand and optimize conversion paths.

A normal use of Markov chain algorithms, has the following set up, as shown in table 5.

Table 4. Markov chain setup

From / To	Ad View	Product Page	Checkout
Ad View	0.0	0.7	0.3
Product Page	0.1	0.0	0.9

These models help businesses predict outcomes and optimize content delivery in real- time, improving ROI and customer satisfaction.

Conclusion of Results

From the analysis, it is evident that social media data plays a transformative role in modern marketing. Engagement metrics provide quantifiable insight into performance, while personalized advertising techniques help deliver targeted content. Mathematical models enable businesses to use large datasets, in order to understand user needs, and dynamically adapt their strategies. As platforms evolve, data related engagement and customization will only become more precise and usfull in digital marketing (Petrescu & Krishen, 2020).

7. Debate

Social media has become a core of modern marketing. In the last decade, it has transformed from a communication tool into a powerful marketing engine. At the heart of this transformation is data, that is collected in huge quantities and is used to support hyper- targeted campaigns that engage users like never before (Basimakopoulou, *et al.*, 2022).

Each day, platforms generate and collect massive volumes of user data. Hidden in this data are insights into what people like, how they behave, and how they respond to content. Analyzing it allows businesses to understand their audience better, retain customers, and fine-tune their strategies for maximum impact. Still, it's not without its challenges. The scale and complexity of data can be overwhelming. Marketing experts need to navigate numerous tools, platforms, and analytical methods. Integrating data across devices and touchpoints also adds another layer of complexity. Yet, for companies that do it right, the benefits, like greater engagement, improved return on investment, and smarter targeting are of great importance.

Despite its advantages, data driven marketing brings serious ethical questions, particularly about privacy. Many users are unaware of how much personal data is being collected or how it's being used. This lack of transparency has led to increased public concern. To address these issues, regulations like the EU's General Data Protection Regulation (GDPR) now require companies to seek user consent and offer control over personal data. Businesses are expected to communicate clearly how data is used, provide optout options, and ensure that data is protected from misuse. Transparency builds trust. Brands that are open and respectful of user data will earn the long-term loyalty of their audience.

Looking ahead, social media analytics will only become more sophisticated. As artificial intelligence (AI) and machine learning (ML) continue to evolve, marketers will gain access to even more detailed data and advanced tools for personalization. Already, AI is helping create content, spot emerging trends, and deliver ads more strategically. Voice and visual search are becoming more revalent, changing how users discover content.

As these technologies mature, businesses will need to keep adapting their strategies to meet changing consumer expectations and platform capabilities. Innovation isn't just about adopting new tools, it's about rethinking how marketing works. The best-performing brands are those that evolve constantly, exploring new platforms, experimenting with interactive formats, and staying in tune with what users want. Whether it's trying out live videos, influencer partnerships, or AI-driven chatbots, staying ahead of trends is essential. But innovation must also extend to how businesses analyze data. The better the insights, the more precise and impactful the messaging (Swart, 2021).

Recent literature underlines that the integration of Artificial Intelligence into data-driven processes brings both strengths and limitations. For instance, Davalas, Charalabidis, and Fenekoy (2022) conducted a SWOT analysis on the use of AI in startup evaluation,

ISSN: 2455-8834

Volume:10, Issue:09 "September 2025"

demonstrating that while AI improves efficiency and accuracy, it simultaneously poses challenges such as high implementation costs and concerns regarding workforce displacement. These findings emphasize that the opportunities and threats of AI adoption are not confined to one domain but are also relevant to social media analytics, where advanced tools for engagement and personalization must be applied with caution and awareness of their constraints.

In short, data analysis is the engine behind today's most effective social media strategies. It empowers brands to make smarter decisions, connect with the right audience, and deliver experiences that feel personal and relevant. As technology continues to progress, the possibilities for innovation are limitless. However, businesses must ensure that their data practices are ethical, transparent, and respectful. By doing so, they'll not only improve performance but also earn trust with their costumers, a key for their success and achievement of long-term goals (Tzavaras & Karamanoli, 2022).

8. Conclusion

In conclusion, the inclusion of social media data analysis in digital marketing campaigns is no longer optional for organizations that want to better connect with their audiences. The findings from this study demonstrate that data-informed methods (with behavioral and retargeting the strongest) can deliver significant improvement in campaign performance and customer conversion. Providers have different definitions and assessments of engagement, but understanding these disparities can help companies further hone content and delivery.

The use of advanced tools like machine learning, NLP, mathematical modeling allows brands to unlock actionable insights from the dark pool of the user behavior. These models are supposed to be not only more optimized for ad targeting but are also designed to predict how end users will behave, how the models will converge and for a certain amount of prediction.

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