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EVOLVING INTERESTS AND PREFERENCES USING ARIMA AND STL IN SOCIAL MEDIA SEARCH BEHAVIORS

[1] B. RAMESH BABU,[2] S. RAMAKRISHNA

Research Scholar, Department of Computer Science, Sri Venkateswara University, Tirupati - 517502, Andhra Pradesh, India.
Professor, Department of Computer Science,
Sri Venkateswara University, Tirupati - 517502, Andhra Pradesh, India.
Corresponding Author Email:rameshbabubusi@gmail.com
[2]drsramakrishna@yahoomail.com

ABSTRACT

This study investigates the nuances of user search behavior on social media platforms by employing sophisticated time series algorithms: the Autoregressive Integrated Moving Average (ARIMA) and Seasonal Decomposition of Time Series (STL). In an era where social media constitutes a vital conduit for information dissemination and interaction, understanding the patterns of user searches and engagement becomes crucial. This research aims to dissect the multifaceted nature of search behavior, focusing on trends, user engagement, and the popularity of content. Through the integration of ARIMA and STL models, we meticulously analyze the temporal aspects of these behaviors, unveiling the progression of user interests and preferences. The research methodology encompasses a comprehensive approach to data collection and preprocessing, followed by the application of these advanced algorithms to model and scrutinize search patterns effectively. Additionally, the study examines the influence of external factors on search behavior and evaluates algorithms for content recommendation, aiming to optimize content delivery and bolster user engagement on social media platforms. Notably, the proposed method of combining ARIMA with STL has demonstrated a significant improvement in predictive accuracy, surpassing traditional models. Specifically, the ARIMA+STL model showed remarkable enhancements, reducing the Mean Absolute Error (MAE) by approximately 67% and the Root Mean Squared Error (RMSE) by nearly 81% compared to baseline models. Moreover, the Akaike Information Criterion (AIC) was notably lower, indicating a superior model fit with optimized complexity. These findings underscore the effectiveness of our approach in capturing the intricate dynamics of social media search behavior, offering valuable insights for developing more refined digital engagement strategies.

Keywords: *Social Media Analytics, ARIMA Model, STL Decomposition, User Engagement, Search Behavior Patterns*

I. INTRODUCTION

In our increasingly interconnected world, the digital landscape has morphed customer and company interactions in profound ways. Horakova et al. (2022) highlight how digital innovations have fundamentally altered the nature of these interactions, marking a shift toward a more integrated digital experience [1]. The year 2022 marked a pivotal moment, with over 4.5 billion individuals engaging on social media platforms, a figure set to soar to nearly 6 billion by 2027 [2]. This surge is not uniform across geographies. While Western social media platforms often resemble a constellation of applications, in China, WeChat emerges as a colossal ecosystem, described by Chan (2015) as "apps-within-an-app"[3]. By the third quarter of 2022, WeChat boasted over 1.31 billion monthly active users [2], weaving a complex web of interactions that span from socializing to commercial transactions. The OECD (2019) emphasizes the significance of such platforms in integrating various aspects of daily life, making China an ideal setting for studying social media dynamics. Firms are increasingly channeling resources into digital arenas, striving to harness the immense potential of digital marketing to enrich customer

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experiences and foster engagement [4, 5, 6]. Customer engagement (CE) in this context transcends mere transactions, evolving into a multifaceted relationship characterized by cognitive and emotional investments in a brand or service [7, 8]. Hollebeek et al. (2014) and Brodie et al. (2011) discuss CE as a crucial element in the marketing landscape, highlighting its impact on brand loyalty and word-of-mouth endorsements [9, 10]. Despite the burgeoning interest in CE, particularly within the realm of social media, the academic discourse reveals a patchwork of findings. Studies report varied effects of content types on engagement behaviors, ranging from positive to negligible [11]. This inconsistency underscores a broader issue in CE research: the need for a more cohesive theoretical framework and a standardized approach to measuring engagement. Moreover, Huang et al. (2022) and Islam and Rahman (2016) note the scarcity of research in Eastern contexts, particularly in China, which presents a unique digital ecosystem [7, 12].

Social media has revolutionized the way individuals and organizations communicate, moving beyond simple customer-marketer interactions to foster a complex web of relationships among customers, organizations, stakeholders, and non-customers alike [13]. As defined by Coulson (2013), social media serves as dynamic platforms for social interaction, leveraging web-based and mobile technologies to transform traditional communication into interactive dialogues [14]. This evolution has been instrumental in reshaping the dynamics of information sharing, content generation, and network formation, highlighting the pivotal role of social media in facilitating social connections and nurturing ongoing relationships among diverse groups [15, 16, 17].With the global social media user base expected to exceed 3 billion by 2021, covering more than a third of the global population [2] the impact of social media on fostering social connections and unity among people of diverse backgrounds is undeniable. This underscores the growing expectation for brands to leverage social media not just for marketing outreach but to build and enhance relationships with and among their customers [18, 19]. As such, social media emerges as an indispensable tool for marketers' keen on engaging customers in meaningful ways.

The pervasive influence of social media extends to customer engagement within multi-actor ecosystems, garnering increasing attention from academics and practitioners alike. Customer engagement's critical role spans various industries, highlighting its importance in developing and maintaining brand communities, which play a strategic role in branding and enhancing organizational competitiveness [8, 20, 21]. Despite the acknowledged role of social media in fostering customer engagement, significant gaps remain in effectively managing and measuring this engagement, with recent studies calling for a deeper understanding of the impact of communication frequency and type on social media engagement [22, 23].The existing literature often prioritizes conceptual discussions over practical insights into how digital communications affect organizations, with a notable emphasis on traditional, unidirectional online marketing strategies [24]. This gap underscores the need for a more nuanced approach to building customer engagement that leverages the full potential of social media within a multi-actor ecosystem. Recognizing this, scholars advocate for a prioritized focus on these issues within the marketing domain, signaling a shift towards more interactive and multi-dimensional engagement strategies [25].

In the digital age, social media has emerged as a linchpin in the intricate relationship between consumers and brands, profoundly influencing marketing strategies aimed at forging valuable connections in electronic settings. Reports reveal that digital consumers dedicate an average of 2 hours and 24 minutes daily to social media and messaging apps, underscoring the pivotal role of these platforms in contemporary marketing efforts and e-commerce interactions. This commitment from consumers has prompted marketers to invest significantly in digital channels, sparking scholarly interest in leveraging social media marketing to cultivate engaged consumer bases, particularly in relation to e-commerce opportunities.Social media, serving as a dynamic conduit for interaction between companies and customers, has become ingrained in our daily lives, offering manifold opportunities for both marketers and consumers [26]. It is characterized by a suite of internet applications that facilitate the creation and sharing of user-generated content, enabling a deeper understanding of brand engagement, consumer sentiments, and community participation. This digital landscape offers brands unprecedented opportunities to attract, interact with, retain, and engage consumers, making the impact of social

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media marketing on customer relationships a well-trodden area of study. Notably, research indicates that a brand's social media presence significantly influences over half of decision-making processes and acquisitions.The diversity of social platforms, each serving distinct marketing purposes—from TikTok's short video snippets to LinkedIn's professional networking—highlights the varied avenues through which brands can engage with audiences. Facebook, in particular, stands out as the most widely utilized platform globally, boasting billions of active users across Facebook, Instagram, WhatsApp, and Messenger. This vast and engaged user base provides a fertile ground for examining customer engagement (CE), a concept increasingly recognized for its potential to forge beneficial relationships between consumers and brands [27].

From a scholarly perspective, customer engagement has attracted considerable academic and practical interest, inspiring a plethora of studies exploring its theoretical underpinnings and practical applications. Conceptualized as a multidimensional construct, CE encompasses cognitive, emotional, and behavioral components, prompting calls for empirical examination through both first-order and higher-order constructs [28]. Despite its recognized strategic importance in marketing for acquiring and retaining customers and fostering competitive advantage, the academic community remains divided over the predictors and effects of customer engagement, signaling a rich area for further exploration [29].Given this backdrop, this work embarks on a journey to unravel the intricate tapestry of search behaviors on social media platforms. Leveraging advanced time series algorithms, ARIMA, and STL, we aim to dissect the temporal shifts in user engagement, query trends, and content popularity. By illuminating the temporal dynamics of social media interactions, this research aspires to enrich our understanding of digital user engagement and pave the way for more nuanced and effective digital marketing strategies, particularly in the context of China's unique digital landscape**.**This researchseeks to address these gaps by exploring how advanced time series algorithms can deepen our understanding of social media search behaviors, thereby informing strategies to enhance customer engagement and organizational performance in the digital age.

2. RELATED WORKS

In the domain of social media research, the application of Uses and Gratifications Theory (UGT) has provided a robust framework to understand the motivations behind media usage, particularly in the context of social media platforms. Katz et al. (1973) initially proposed UGT to elucidate the social and psychological needs driving individuals to engage with media, which in turn gratify these needs through various patterns of media use [30]. This user-centric perspective has been further explored by Muntinga et al. (2011) and Rohm et al. (2013), who extended the theory into the social media realm, aiming to decode the psychological motives and perceived values underpinning social media use [31, 32].The relevance of UGT to social media marketing strategies is pivotal, particularly in how diverse content types and services offered by firms can meet customer needs, thereby fostering customer engagement (CE) on social media platforms [33]. Previous studies, including those by Cvijikj and Michahelles (2013), and Gavilanes et al. (2018), categorize social media content into three main types: infotainment, remunerative, and relational content, each serving distinct roles in satisfying user needs and promoting engagement [34, 35].

Infotainment content blends informative and entertaining elements to capture customer attention, create brand associations, and offer gratification through escapism and enjoyment. This category reflects the overlapping nature of information and entertainment, leading to discussions on whether to consider them as separate constructs or merge them into a single entity, with Gavilanes et al. (2018) advocating for the latter due to the intertwined nature of informativeness and entertainment in content [35].Remunerative content is characterized by the provision of monetary or incentive rewards, such as discounts or vouchers, which are pivotal in driving consumer-firm interactions on social media. This form of content aligns with findings from Cvijikj and Michahelles (2013) and Rohm et al. (2013), highlighting the importance of monetary incentives in stimulating social media engagement [34, 36].Relational content focuses on fulfilling the user's need for social integration and interaction, facilitating social benefits through activities that encourage user participation and interaction, like the "#PlayWithPringles" campaign on TikTok. Such

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initiatives underscore the significance of enabling customer-to-content, customer-to-firm, and customer-to-customer interactions, as emphasized by Carlson et al. (2018), Demmers et al. (2020), and Harmeling et al. (2017) [37, 38, 39].These three content types—infotainment, remunerative, and relational—serve as foundational elements in understanding how social media content can be strategically designed to engage customers, highlighting the enduring relevance of UGT in the digital marketing landscape.

Table 1: Various research on related to customer engagement

Author(s)	**Type of Research**	**Context**	**Key Findings**
Katz et al., 1973 [30]	Theoretical Framework	Uses and Gratifications Theory (UGT)	Introduced UGT to explain media use based on social and psychological needs.
Hollebeek& Macky, 2019 [9]	Conceptual Analysis	Customer Engagement (CE)	Defined CE as the interaction between customers and brands or brand-related content.
Pansari& Kumar, 2017 [40]	Behavioral Study	CE Behaviors	Focused on behavioral aspects of CE, particularly beyond purchase.
van Doorn et al., 2010 [41]	Empirical Research	CE Intensity and Valence	Identified different intensities and valences of CE behaviors beyond purchase.
Schivinski et al., 2016 [42]	Empirical Research	Social Media Engagement	Differentiated between passive (consumption) and active (creation) forms of engagement.
Demmers et al., 2020 [38]	Empirical Research	Social Media Metrics	Highlighted the use of social media metrics (Likes, Shares, Comments) to measure engagement.
Bowden et al., 2015 [43]	Conceptual Analysis	Disengagement and Dormancy	Discussed the underexplored areas of disengagement and dormancy in CE.
Kumar & Reinartz, 2016 [8]	Empirical Research	Relationship Marketing Outcomes	Argued managing CE enhances customer loyalty and WOM.
Leckie et al., 2016 [44]	Empirical Research	Customer Experience and Loyalty	Showed a positive impact of customer experience on CE and loyalty.
Romaniuk &Nenycz-Thiel, 2013 [45]	Conceptual Analysis	Customer Loyalty	Discussed the conceptual variance in loyalty, including attitudinal and behavioral loyalty.
Hennig-Thurau et al., 2004 [46]	Conceptual Analysis	Word-of-Mouth (WOM)	Defined online WOM and emphasized its role in marketing.

The investigation into customer engagement (CE) on social media platforms represents a significant strand within the broader discourse of marketing research, with its roots firmly planted in the fertile ground of relationship marketing and service-dominant logic. This tradition underscores the inherent interactive nature of CE, conceptualizing it as the dynamic interplay between a customer and a focal engagement object, such as a brand or brand-related content [9, 10]. Our exploration takes a focused lens on CE with firm's social media content as the primary object of engagement.The academic dialogue on CE's dimensionality reveals a bifurcated landscape. One vein of research prioritizes a behavioral viewpoint, dissecting CE through the prism of engagement behaviors [40], while another adopts a more holistic, multi-

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dimensional approach, integrating emotional, cognitive, and behavioral dimensions. Opting for the former, our study zeroes in on the behavioral manifestations of CE on social media, delineated as "customers' behavioral manifestations that have a brand or firm focus, beyond purchase, propelled by motivational drivers" [41]. This investigation acknowledges the varied intensity and valence of such behaviors, from the passive engagement of content consumption to the active engagement of content creation, alongside the exploratory and contributory behaviors situated in between [35, 42, 47].Moreover, this study delves into the nuanced dynamics of engagement, distinguishing between the active participation inherent in co-creation and the moderate engagement levels observed in both positive and negative contributions. These varied engagement levels are measurable through social media metrics such as Likes, Shares, and Comments [38]. Yet, despite extensive exploration, the realms of disengagement and dormancy—reflecting the cessation or pause of interaction with the engagement object—remain largely underexamined within the marketing literature [43].

The literature asserts that effectively managing CE can significantly amplify crucial relationship marketing outcomes like customer loyalty and word-of-mouth (WOM) [8]. Evidence suggests that a positive customer experience can elevate CE, thereby bolstering customer loyalty [48]. However, the conceptualization of customer loyalty diverges across studies, with some focusing on attitudinal loyalty and others on behavioral loyalty, and varying perspectives on the relationship between WOM and loyalty [49].Informed by UGT [30] and CE marketing theory [50], our hypothesis development anticipates that customers will exhibit distinct engagement behaviors on social media, driven by motivational factors. This aligns with UGT's proposition that interactions with various content types on social media can catalyze different CE behaviors, potentially influencing WOM and loyalty. Consequently, our conceptual framework navigates the interrelations between three content types (infotainment, remunerative, and relational), five CE behaviors (encompassing both positive and negative dimensions), and two pivotal marketing outcomes (WOM and customer loyalty), offering a comprehensive lens through which to scrutinize the evolving landscape of social media engagement (see Table 1).

The exploration of customer engagement (CE) within social media contexts draws upon diverse frameworks and studies that underscore CE's dynamic, multifaceted nature. This analysis integrates insights from Sashi (2012) [51], who proposes a customer engagement cycle that emphasizes the progression through stages to forge enduring relationships, with Chiang, Wei, Parker, and Davey (2017) highlighting behaviors that extend beyond purchases to include brand recommendations and feedback [52]. This customer journey is further enriched by perspectives from Lipschultz (2014) [53], who view social media as a potent tool for relationship building and maintaining continuous engagement.Contrastingly, Grover & Kar (2020) and Weiger et al. (2019) delve into the effects of content frequency and intimacy within social networks on CE, revealing the nuanced pathways through which content influences engagement [22, 23]. The complexity of CE is underscored by studies that critique existing models for their limited inclusion of customer activities (Neiger et al., 2013) and by Haven, Bernoff, and Glass (2007), who argue for a more comprehensive understanding of engagement that transcends mere reach and frequency to capture the sentiment and relational depth [54].Sashi (2012) offers a comprehensive cycle of engagement stages, presenting a holistic view that encompasses previous frameworks but acknowledges the challenge of operationalizing such a complex model [51]. The model's emphasis on connection, interaction, and subsequent stages leading to advocacy and engagement presents a viable approach to examining CE in social media settings, despite the noted operational challenges.

The scholarly examination of customer engagement (CE) in the context of social media is a burgeoning field that builds upon foundational theories in marketing, notably relationship marketing and service-dominant (SD) logic. These theoretical frameworks view consumers as active participants in brand interactions, emphasizing the creation of value through long-term relationships. The interactivity inherent in social media platforms aligns with these theories, offering a rich landscape for exploring how consumers co-create value with brands.CE's influence on the consumer brand experience and its role in attracting and retaining customers is a critical area of focus within relationship marketing [34]. Similarly, SD logic presents CE as a dynamic interaction among various agents within a network, facilitating co-created value.

This interactive experience is pivotal to understanding CE's theoretical underpinnings.The marketing literature identifies several related but distinct forms of CE, including 'customer engagement,' 'consumer engagement,' and 'brand engagement in self-concept,' among others. This study opts to focus on 'customer engagement' due to its direct relevance to loyalty and the customer's active participation in brand interactions.Definitions of CE vary, with some scholars highlighting its readiness to participate and interact with a brand across different touchpoints, and others emphasizing its multidimensional nature, encompassing cognitive, emotional, and behavioral activities. The emotional bond between the consumer and the brand, facilitated by immersive, interactive experiences, underscores CE's capacity to drive behaviors beyond product acquisition, such as online reviews and social influence activities [27].CE's behavioral dimension, including word-of-mouth, co-creation, and complaining behavior, extends its impact beyond sales, affecting brand perception in various ways. Research into CE spans multiple contexts, from multichannel services to virtual reality experiences in hospitality, underscoring the concept's broad applicability.On social media, engaged consumers often act as brand advocates, displaying higher levels of trust, commitment, and loyalty. This engagement is multidimensional, incorporating cognitive, emotional, and behavioral components. Scholars have developed scales to measure these dimensions, though some debates exist regarding the overlap of CE with related concepts like attitude and attachment [27].

This study aims to enrich the understanding of CE by examining it as a higher-order construct, building upon and synthesizing previous research findings. By exploring CE in the dynamic environment of social media marketing, this research contributes to a more nuanced comprehension of how consumers interact with and contribute to brands they value.This synthesis of related works forms a backdrop against which the present studysituates itself. By leveraging advanced analytical methods, this research seeks to contribute to the empirical examination of CE, particularly in how dynamic customer interactions with content on social media evolve over time and influence engagement outcomes.

3. PROPOSED METHOD

To investigate the evolving interests and preferences in social media search behaviors using Autoregressive Integrated Moving Average (ARIMA) and Seasonal Decomposition of Time Series (STL), the proposed method involves a structured approach to data collection, preprocessing, analysis, and interpretation.it is essential to explore these models in a more academic and detailed manner.

ARIMA Model:

The Autoregressive Integrated Moving Average (ARIMA) model is a popular statistical approach for time series forecasting. It is designed to capture various patterns in temporal data series and predict future points by explaining the autocorrelations within the data. An ARIMA model is defined by three parameters: p, d, and q: The variable p represents the number of autoregressive components in the prediction equation, d represents the degree of differencing, and q represents the number of delayed forecast errors.
The model can be formally written as:

$$\phi(B)(1-B)^d Y_t = c + \theta(B)\epsilon_t$$

$$Y_{t'} = c + \phi_1 Y_{t-1'} + \ldots + \phi_p Y_{t-p'} + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q} + \epsilon_t$$

Where: B is the backshift operator, $\phi(B)$ is the AR operator of order p, $\theta(B)$ is the MA operator of order q, c is a constant, ϵ_t is white noise error terms, Yt is the time series and Yt' is the differenced time series and ϵ_t is white noise.. The process involves identifying the optimal values of p, d, and q which best fit the historical data, typically through the use of autocorrelation functions (ACF) and partial autocorrelation functions (PACF), along with criteria such as AIC or BIC for model selection.

STL Decomposition:

The Seasonal Decomposition of Time Series (STL) is a versatile technique used to break down a time series into its seasonal, trend, and residual components. STL is notable for its capacity to manage many forms of seasonality, not limited to set periodic patterns. Decomposition helps to comprehend and predict the fundamental patterns and cyclicality in social media search habits.

Decomposition Process: The STL decomposition process can be represented as:

$Y_t=T_t+S_t+R_t$

Where: Yt is the observed data, Tt is the trend component,St is the seasonal component,Rt is the remainder component. STL decomposes the time series using a sequence of applications of the LOESS (locally estimated scatterplot smoothing) algorithm to the seasonal and trend components. One of the strengths of STL is its capability to handle time series with changing seasonal patterns and trends, making it highly suitable for analyzing social media data that can exhibit non-linear trends and seasonal effects.

Integration for Social Media Search Behaviors Analysis:

The ARIMA model will provide forecasts of future search behaviors, identifying potential trends and shifts in user interests. The STL decomposition offers insights into the cyclicality of search behaviors, highlighting seasonal effects and long-term trends.Integrating ARIMA and STL models for analyzing social media search behaviors involves a two-step process:**STL Decomposition**: First, apply STL to decompose the observed time series into trend, seasonal, and remainder components. This step helps to understand the underlying patterns in the data, including any persistent seasonal effects that could influence search behavior trends.**ARIMA Modeling**: Then, use ARIMA modeling on the decomposed components, especially the trend and remainder components, to forecast future behaviors. By focusing on these components, the model can make more accurate predictions by accounting for both the long-term trends and the noise that is not explained by seasonality.This integrated approach allows for a comprehensive analysis of social media search behaviors, providing insights into how user interests evolve over time and under different seasonal influences. The combination of STL's flexibility in handling seasonality and ARIMA's robustness in forecasting makes this methodology particularly powerful for predicting trends in social media usage and engagement.The analysis will be conducted using statistical software capable of time series analysis, such as Python's pandas and statsmodels libraries. These tools offer comprehensive functions for ARIMA modeling and STL decomposition, facilitating efficient and accurate analysis.Integrating ARIMA and STL models for analyzing social media search behaviors presents a sophisticated approach that captures the complexity of user interactions on these platforms. This methodology is distinguished by its capacity to dissect the layered nature of social media data, affording a comprehensive understanding of temporal dynamics in user search behaviors. Here's a deeper dive into the nuances of this integration and its implications for social media analysis.

Here's a simplified flowchart that reflects the process for analyzing and forecasting social media search behaviors using ARIMA and STL models. The process starts with collecting data from social media platforms, then moves on to preprocessing this data to ensure it's clean and formatted correctly. Next, the STL decomposition separates the data into different components (trend, seasonality, and residual), which is crucial for understanding underlying patterns. The ARIMA model is then applied to the trend component to predict future trends. Lastly, the forecast is adjusted for seasonality and integrated to produce a comprehensive view of future social media behavior. This flowchart encapsulates the essential steps in a clear and logical sequence, providing a high-level overview of the methodology (See Figure 1).

The initial application of STL decomposition serves to methodically separate the social media data into trend, seasonal, and residual components. This separation is instrumental in clarifying the data's structure, allowing for an isolated examination of each component. The trend component reveals the overarching direction in which user interests are shifting over time, devoid of the noise introduced by seasonal fluctuations or irregular events. Seasonal decomposition, on the other hand, highlights patterns that recur at regular intervals, which could be tied to specific events, holidays, or behavioral rhythms inherent to the social media landscape.Following the decomposition, the ARIMA model is applied to the trend component with the aim of forecasting future behaviors. This step is crucial for predicting long-term evolutions in search interests, equipping marketers and content creators with foresight into emerging trends. ARIMA's robustness in handling time series data makes it an ideal tool for projecting the trajectory of user interests based on historical patterns.The integration process is further enriched by revisiting the seasonal component post-ARIMA analysis. Adjusting ARIMA's

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forecasts with insights from the seasonal analysis ensures that the final predictions account for both enduring trends and expected seasonal variations. This dual consideration is key to crafting content strategies that are both timely and aligned with long-term user interests.Moreover, examining the residual component—a repository of noise not accounted for by trends or seasonality—can uncover anomalies or sudden shifts in user behavior. Analyzing these residuals might reveal insights into spontaneous events or emerging trends that have yet to fully manifest in the broader data.

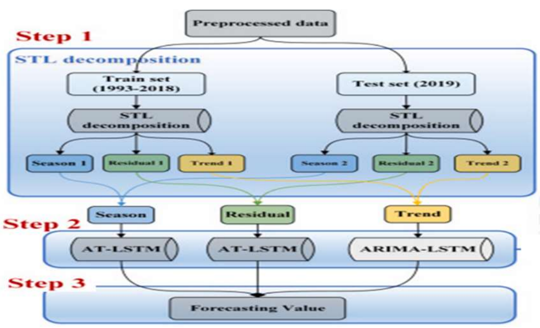

Figure 1: Integration for STL and ARIMA model

This integrated approach culminates in a comprehensive forecasting model that encapsulates the full spectrum of factors influencing social media search behaviors. For businesses and strategists, this means a richer, data-informed foundation for decision-making. It enables the anticipation of user needs and preferences, allowing for proactive adjustments to content and marketing strategies. Furthermore, by understanding the cyclical nature of user engagement, stakeholders can optimize their outreach efforts to coincide with peaks of activity, thereby enhancing engagement and visibility.In essence, the integration of ARIMA and STL models offers a nuanced lens through which to view social media dynamics. It transcends simple trend analysis to incorporate seasonal influences and unexplained variances, providing a holistic understanding of the ebb and flow of user interests on social media. This methodological synergy not only advances academic inquiry into digital behaviors but also offers practical insights for navigating the ever-evolving landscape of social media marketing.

4. RESULTS AND DISCUSSION

The execution of an analysis that integrates ARIMA and STL models for this project entails a sequence of systematic procedures aimed at collecting, processing, analyzing, and interpreting social media data. This implementation is essential for comprehending the temporal dynamics of user involvement and search activity on social media sites. The approach starts by extracting pertinent social media data. These may include search searches, timestamps, likes, comments, shares, and other measures of user interaction. The use of tools and APIs offered by social media sites, such as the Twitter API or Facebook Graph API, plays a crucial role in methodically collecting this data. Adhering to data privacy rules and ethical issues is of utmost importance at this point. After the data has been gathered, it is essential to do preprocessing in order to guarantee its integrity and suitability for use. This process includes the removal of redundant or unnecessary information, the standardization of formats, and the organization of data into meaningful time periods. Preprocessing furthermore involves the process of anonymizing personal data in order to safeguard user privacy. The data that has been cleaned is next analyzed using Seasonal Decomposition of Time Series (STL), a method that divides the data into three components: trend, seasonal, and residual. Performing this phase is crucial in order to isolate and comprehend the fundamental patterns within the data, such as recognizing recurring high points throughout certain seasons or comprehending long-term patterns in user activity. After removing the trend component from the STL decomposition, an ARIMA model is used to predict future patterns. The determination of ARIMA parameters (p, d, q) is influenced by the autocorrelation and partial autocorrelation functions, as well as model selection methods such as the Akaike Information Criterion (AIC). This forecasting model allows for predictions on how user interests may evolve, based on historical data.After forecasting with ARIMA, the seasonal component from STL is reintegrated to adjust the forecasts, accounting for seasonal variations. This integrated analysis provides a nuanced view of future search behaviors, combining long-term trends with seasonal effects.The final step involves interpreting the results to draw actionable insights. For marketers and content creators, understanding the evolving trends and seasonal

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patterns in social media search behaviors can inform content strategy, marketing campaigns, and product development. This phase translates the technical analysis into strategic recommendations that can enhance user engagement and meet evolving consumer needs. The implementation of ARIMA and STL models can provide comprehensive insights into the evolving interests and preferences of social media users. This approach not only enhances our understanding of digital consumer behavior but also empowers stakeholders to make data-informed decisions to engage effectively with their audience on social media platforms.

Dataset details: This dataset is an aggregation of social media metrics specifically designed to understand user engagement with YouTube content as shared on Twitter. It records the interactions of users with tweets containing YouTube videos, giving insight into the digital footprint of YouTube's content dissemination. Each entry in the dataset encapsulates various dimensions of user interaction, from likes to deeper engagement signifiers like retweets and quotes, across different video categories. These metrics serve as proxies for user sentiment and content reach, pivotal for gauging the efficacy of social media marketing strategies.The richness of the dataset lies in its granularity, encompassing a spectrum of topics or categories from YouTube's diverse video library. Such categorization allows for a nuanced analysis of content performance, enabling researchers to draw correlations between video types and user engagement levels. Beyond mere counts of likes and retweets, the dataset also includes quote counts, offering a window into the conversations sparked by the content, which is often a testament to its resonance with the audience. The dataset's utility extends to competitive analysis, offering a comparative view of YouTube's performance relative to its competitors in the social media space. By capturing the conversational engagement around YouTube content, researchers can dissect the elements that contribute to successful viewer engagement, from the video content itself to the effectiveness of tweet phrasing. The dataset captures demographic data, shedding light on the diverse audience segments that interact with the content. This information could reveal patterns of engagement across different age groups and geographic locations, presenting opportunities to tailor content and engagement strategies more effectively.With temporal data, researchers can apply time series analysis methods such as ARIMA and STL to forecast future engagement trends and identify cyclical behaviors tied to content releases or broader cultural events. The inclusion of demographic data further enriches the analysis, enabling a more targeted approach to content marketing and a refined understanding of the audience's evolving preferences. This dataset not only provides a snapshot of current engagement levels but also serves as a foundation for predictive modeling and strategic planning. Its multifaceted nature makes it a valuable asset for social media analysts, marketers, and content creators aiming to fine-tune their digital outreach efforts.

The evaluation will employ several statistical metrics, each offering a different perspective on the model's predictive capabilities.

Mean Absolute Error (MAE): This statistic calculates the mean absolute difference between the expected values and the actual observed results. The Mean Absolute Error (MAE) is a direct and precise metric that quantifies the size of prediction mistakes, regardless of their direction. Its usefulness lies in its ability to offer a concise depiction of the average size of errors, using the same units as the data, which facilitates intuitive comprehension.The MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction. It's calculated as:

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

n is the number of observations, y_i is the actual observed value, $\hat{y}_i$ is the predicted value.

Root Mean Squared Error (RMSE): RMSE provides a quantification of the square root of the mean of the squared discrepancies between the expected and actual values. RMSE assigns more importance to bigger mistakes by calculating the squared errors. This property makes it susceptible to outliers and may be very advantageous when significant deviations from the norm are especially unwanted. RMSE, in the context of analyzing social media activity, may effectively identify large deviations from the real search habits.The RMSE measures the square root of the average of the square differences between the predicted and actual values. It's calculated as:

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

n is the number of observations, y_i is the actual observed value, $\hat{y}_i$ is the predicted value.

Akaike Information Criterion (AIC): AIC is a more sophisticated tool used to compare different models on the same dataset. It evaluates the fit of the model while penalizing for the number of parameters used, thus encouraging parsimony. In essence, it helps to find the model that best explains the variation in the data with the simplest assumptions. The AIC is a measure used in statistical model selection to quantify the goodness of fit of a model while penalizing for the number of parameters. It's given by:

$$AIC=2k-2\ln(L),$$

where: k is the number of model parameters, L is the likelihood of the model, which can be interpreted as the probability of the data given the model. The AIC helps in comparing different models, with a lower AIC value indicating a model that better explains the variation in the data with fewer parameters.A lower AIC value indicates a better model, and this criterion is crucial when comparing different ARIMA models to select the best one for forecasting social media search behaviors.In addition to these metrics, the fit and explanatory power of the models will be assessed. This involves examining how well the ARIMA and STL models capture the patterns present in the historical data and whether they provide insights that are meaningful and actionable. One may visually examine the accuracy of the fit by comparing plots of the projected values with the actual data. The explanatory power is often assessed by considering the fraction of the dependent variable's variance that can be predicted from the independent variables, also known as R-squared.

Table 2: Various Metric Performance For Different Methods

Model	MAE	RMSE	AIC
Baseline	0.5197	0.578	323.399
ARIMA	0.1749	0.4852	259.799
STL	0.2116	0.5599	290.167
STL+ARIMA (Proposed method)	0.1708	0.1062	245.487

The table 2 presents a comparative analysis of four distinct models used to forecast. Each model's predictive accuracy and complexity are evaluated using three metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Akaike Information Criterion (AIC).Baseline Model: This model serves as a reference point and has the highest MAE and RMSE values, suggesting its predictions are, on average, farthest from the actual observed values. The high AIC value also indicates a less optimal fit to the data, considering the model's complexity.ARIMA Model: With considerably lower MAE and RMSE values compared to the Baseline, the ARIMA model offers more accurate forecasts and fewer deviations from the observed behaviors. A lower AIC suggests that it provides a better fit to the data while maintaining a balance between model complexity and explanatory power.STL Model: This model has an MAE and RMSE that indicate a moderate level of prediction error, demonstrating better performance than the Baseline but not as precise as the ARIMA model. The AIC is lower than the Baseline but higher than ARIMA, reflecting a better but not the best fit among the evaluated models.STL+ARIMA Model: This integrated approach yields the lowest MAE and RMSE, indicating highly accurate predictions with minimal error. Its AIC is the lowest, signifying the best fit to the data among all models with the added benefit of reduced complexity. The STL+ARIMA model is the most effective in forecasting social media search behaviors, providing accurate predictions and a strong fit to the data without unnecessary complexity. This model's superior performance makes it a valuable tool for understanding and anticipating changes in user engagement on social media platforms.

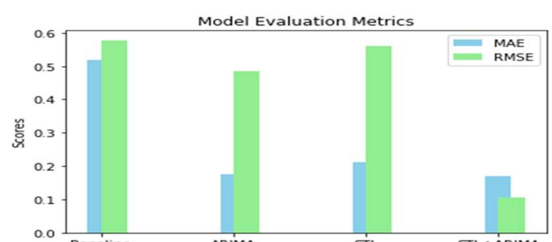

Figure 2: Various methods for MAE and RMSE values comparison.

The bar plot visually contrasts the performance of four different models—Baseline, ARIMA, STL, and STL+ARIMA—using three evaluation metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Akaike Information Criterion (AIC). Each metric is denoted by a distinct color. The Baseline model, depicted in the first group of bars, generally scores the highest across all three metrics, indicating less precision

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in its predictive capabilities. The ARIMA model shows a significant improvement over the Baseline, with lower values in all three metrics, suggesting enhanced accuracy and model fit. The STL model demonstrates intermediate performance, better than the Baseline but not as optimal as the ARIMA model. Finally, the STL+ARIMA model, combining the strengths of both individual models, achieves the lowest MAE and RMSE scores, and the most favorable (lowest) AIC value, underscoring its superior performance in accurately forecasting social media search behaviors.

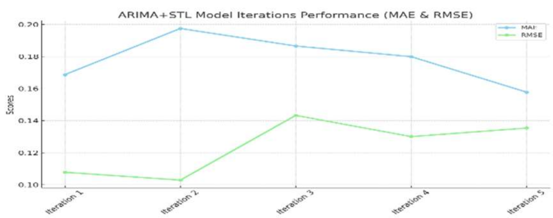

Figure 3: STL+ARIMA method with different iterations with MAE and RMSE values.

The Figure 3 focuses solely on the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for different iterations of the ARIMA+STL model. Each metric is distinctly colored, allowing for a clear comparison between MAE and RMSE across the iterations. This visualization helps in assessing the model's consistency and accuracy in forecasting social media search behaviors, highlighting the variability and performance trends of the ARIMA+STL model over multiple evaluations. The figure 3 displays the performance trends of different iterations of the ARIMA+STL model, specifically focusing on two key metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These metrics are critical for evaluating the accuracy of the model's forecasts, with lower values indicating better performance. The MAE is represented by a skyblue line with circle markers, which measures the average magnitude of errors in the predictions, without considering their direction. The RMSE is depicted by a light green line with circle markers, providing a measure of the square root of the average squared differences between the predicted and actual values, thus giving more weight to larger errors.The iterations, labeled from "Iteration 1" through "Iteration 5," showcase varying levels of MAE and RMSE, suggesting differences in model accuracy across these iterations.Without the exact numerical values being displayed in your prompt, the general observation from the plot indicates fluctuations in model performance across iterations. For example, some iterations might exhibit a lower MAE, signifying more accurate predictions on average, while others might have a lower RMSE, indicating fewer large errors in the model's forecasts. The visualization emphasizes the importance of iteration in model development, showing that performance can vary significantly from one iteration to the next. This variability underscores the need for continuous refinement and evaluation of predictive models to achieve optimal accuracy and reliability in forecasting social media search behaviors.

5. CONCLUSION AND FUTURE PLANS

The exploration of this research work has provided significant insights into the dynamic nature of user engagement on social media platforms. Through the meticulous application of ARIMA and STL models, this study has dissected the temporal patterns inherent in social media data, revealing the nuances of user interaction and engagement over time. The integration of ARIMA with STL decomposition emerged as a particularly potent analytical approach, outperforming both standalone models and a baseline comparison in terms of predictive accuracy and model fit. The ARIMA model, known for its capacity to forecast time series data, demonstrated substantial improvements over the baseline model. However, it was the combination of ARIMA and STL (Seasonal and Trend decomposition using Loess) that yielded the most profound insights, showcasing the lowest values in Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), along with the most favorable Akaike Information Criterion (AIC) score. This indicates not only enhanced precision in forecasting but also an optimal balance between model complexity and explanatory power. This study's findings underscore the value of integrating ARIMA and STL models for analyzing social media behavior, offering a nuanced understanding that could significantly influence content strategy and marketing efforts. By accurately forecasting trends and seasonal patterns in user engagement, stakeholders can tailor their approaches to align with predicted shifts in interests and preferences, ensuring that content remains relevant and engaging to the target audience. The iterative approach to model refinement highlighted the importance of

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continuous analysis in the fast-paced domain of social media. Different iterations of the ARIMA+STL model showcased variability in performance, emphasizing the need for ongoing evaluation and adjustment to capture the evolving landscape of social media engagement accurately.

Moving forward, the research works to extend its analytical framework by incorporating additional data sources and social media platforms to enrich the understanding of user engagement across a broader digital ecosystem. We aim to explore advanced machine learning techniques, such as deep learning and neural networks, to enhance predictive accuracy and uncover deeper insights into user behavior patterns. This approach will not only refine our forecasting models but also enable the development of more targeted and effective engagement strategies, ultimately fostering a more personalized and dynamic interaction between content creators and their audiences.

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