Forum for Linguistic Studies 2024, 6(2), 1184.
https://doi.org/10.59400/fls.v6i2.1184

Article

Impact of social media on the evolution of English semantics through linguistic analysis

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CITATION

Shen Y. (2024). Impact of social media on the evolution of English semantics through linguistic analysis. Forum for Linguistic Studies. 6(2): 1184. https://doi.org/10.59400/fls.v6i2.1184

ARTICLE INFO

Received: 5 February 2024
Accepted: 7 March 2024
Available online: 20 March 2024

Abstract: Social media (SM) influences social interaction in the age of digital media, impacting how languages develop. Since these networks play a role in daily life, they create new words and conceptual frameworks that define our contemporary society. The current investigation investigates Twitter, Facebook, and Reddit SM posts applying textual extraction. The seven-year temporal sample demonstrates significant semantic change caused by society and technology. The analysis notices the importance of new words, phrase meaning evolving, and sentiment changes in SM users' English usage, proving their adaptability. The growing popularity of phrases like eavesdropping and doom-scrolling indicated how SM and daily life impact. This investigation distinguishes each platform's unique linguistic features and digital developments by understanding language flow and leading research in the future.

Keywords: English semantics; linguistic analysis; social media texts; social media networks; digital communication

1. Introduction

Social media (SM) has impacted interpersonal relationships and language application. SM networks' complex English vocabulary represents technological advances and the constant transformation of social expression Zhou (Zhou et al., 2021). This linguistic evolution embodies today's technical environment as it impacts the semantics of the English language (Chauhan et al., 2020). The development of new lexical databases, the reshaping of existing ones, and the global adoption of informal vocabulary prove this language change (Ulugbek, 2021; Toirova and Hamroeva, 2020). Modern linguistics studies use language development in online discourse to address this evolution (Armon-Lotem et al., 2020; Kotowski, 2020; Kumar et al., 2022).

Virtual communication affects language by terminologies, lexical changes, and keyword implications, based on the most recent research (Borkar et al., 2023). Enormous user-generated volumes of data allow linguistic analysis, impacting this rapidly developing industry. A few investigators (Alnuaim et al., 2022) apply machine learning techniques for assessing massive amounts of data, while other researchers utilize qualitative analyses to obtain findings on how languages function. Despite the advancements in the field (Kimmatkar and Babu, 2021; Balajee et al., 2021), it also faces challenges primarily due to the transient and volatile nature of online language trends. The velocity at which new vernacular emerges and diffuses presents a moving target for researchers (Mannepalli et al., 2022; Depuru et al., 2022). The informal and idiosyncratic use of language on SM platforms resists standardization, complicating efforts to systematically categorize and analyze linguistic phenomena (Sekhar et al., 2021).

The motivation behind the proposed work is to bridge the gap between the ephemeral nature of online linguistic trends and the analysis required to understand them. Recognizing the limitations of current methodologies, it is found that there is a need for an approach that captures the transient lexicon of digital discourse and provides a framework for its systematic analysis (Durga and Rajesh, 2022). Through this, the work aims to find insights into the implications of language evolution on SM to contribute to the academic discourse and provide a reference point for future linguistic studies (Ashok Kumar et al., 2021). The proposed work introduces a comprehensive methodology that incorporates both breadth of corpus linguistics and depth of discourse analysis. The work employs computational tools to manage large-scale data from SM platforms while applying rigorous linguistic frameworks to discern patterns and shifts in semantics. The approach is designed to be adaptable, accounting for the rapid evolution of language online and ethically sound, respecting the privacy of individuals. By combining quantitative and qualitative methods, the proposed work provides an understanding of how English semantics are evolving in the age of digital communication by identifying the intricate relationship between language, technology, and society.

The paper is organized as follows: section 2 presents a literature review, section 3 presents a methodology, section 4 presents the analysis, and section 5 concludes the work.

2. Literature review

The emergence of SM has shown a paradigm shift in communication that has simultaneously enriched and complicated language dynamics (Bharti, S. K., et al. 2022). In recent years, the spread of misinformation on platforms like Sina-Weibo has increased, which is the scope of study in Thirumuru et al. (2022) and Kumar et al. (2023), in which they are involved in exploring the dissemination patterns driven by new linguistic characteristics that are persuasive and uncertain words in particular. They show the influence of imagery in amplifying the effects that resonate with the challenge of discerning truth in the digital age. Srinivas and Mishra (2022), Mishra and Srinivas (2021), Setiawan et al. (2022) examine SA techniques in predicting electoral outcomes based on SM moods.

This overview highlights sentiment analysis's (SA) capability to accurately represent public views on politics and its benefits and drawbacks. The primary focus of Irrinki (2021), Lakshmi et al., (2023), Madhavi et al. (2023) is on the psychological significance of words and the probability of how they can change as an outcome of current political and social currents. The research conducted found that societal views impact phrase sentimental qualities over time (Nanduri et al., 2023; Srinivas et al., 2023; Sugumar et al., 2023).

Applying the Uzbek language, perform studies to investigate the significance that machines in the field of linguistics perform in natural language processing (NLP) for artificial intelligence (AI) (Kuchibhotla et al., 2023). Their studies highlight the requirement for linguistic frameworks that deal with unique languages' syntactic and semantic features (Chintalapudi et al., 2023). The bilingual development of language research demonstrates that English-Hebrew-speaking kids have an understanding.

Their findings show that asymmetric linguistic systems are shaped by age and the onset of bilingualism. It shows that the grammatical knowledge is robust, whereas the lexicon is susceptible to bilingual influence. Dimlo et al. (2023) challenges existing semantic analyses of the English locative prefix "out", using a corpus-based approach to question the validity of previously proposed restrictions. The study shows the prefix's flexibility and underscores the complexity of forming a comprehensive semantic account.

3. Methodology

The proposed work employs the corpus analysis model to investigate the impact of SM on the evolution of English semantics. Corpus analysis is a method in the field of linguistics that involves the examination of a large body of text (corpus) to detect patterns, trends, and changes in language use over time.

(i) data collection:

The data source for the work is textual content extracted from three prominent SM platforms: Twitter, Facebook, and Reddit. The study encompasses a wide range of content types to ensure a comprehensive linguistic analysis, including (a) posts and status, (b) comments and replies, (c) hashtags and trending topics, and (d) thematic threads. The data sourced had spanned seven years, supporting analysis for both short-term trends and more sustained shifts in language use. To ensure consistency, the data collected underwent the following processing steps.

(ii) Data processing

Data processing in this study involves a series of steps to transform raw SM text into a structured and analyzable corpus. This process ensures that the data is representative of SM communication and suitable for linguistic analysis. Once extracted, the data undergoes cleaning; this involves:

- Removing non-textual elements: Stripping emojis, images, URLs, and other non-textual components.
- Anonymization: Redacting user names and other personally identifiable information to adhere to privacy and ethical standards.
- Normalization: Standardizing variations in language use, such as different spellings or informal contractions, and also maintaining the integrity of the original text.

Text preprocessing prepares the data for corpus analysis. This includes:

- Tokenization: Breaking down the text into individual words or tokens.
- Part-of-speech tagging: Assigning parts of speech (e.g., noun, verb, adjective) to each token.
- Lemmatization: Reducing words to their base or dictionary form (lemmas).

(iii) Corpus construction

The construction of the corpus involved the following steps: Firstly, using an automated script (**Figure 1**), the work scrapes textual data from the selected platforms. The collected data was then cleaned to remove non-linguistic elements such as emojis, URLs, and usernames through the above-mentioned preprocessing process. The processed texts are then compiled into a structured corpus by organizing the data in a format accessible and analyzable by the corpus analysis software. The corpus is segmented based on source platform and content type (posts, comments, threads) to allow for comparative analysis across different data segments. The resulting corpus contains approximately 2.86 million words, and the description of the corpus constructed on the textual data sourced from three platforms is shown in **Table 1**.

```
    str: Cleaned text.
    """
    # Remove emojis and URLs
    text = re.sub(r'[^\w\s]', '', text)
    text = re.sub(r'http\S+', '', text)

    # Additional cleaning and anonymization steps can be ad

    return text

# Example usage
url = 'https://www.example-social-media.com/user-posts'
scraped_text = scrape_social_media(url)
print(scraped_text)
```

Figure 1. Code snippet of the text scrapping script.

Table 1. Corpus description.

SM platform	Data collected (words)	Data after processing (words)
Twitter	1,023,456	973,456
Facebook	987,654	938,654
Reddit	849,210	788,210
Total	2,860,320	2,700,320

To ensure the reliability of the corpus, random samples of the corpus are inspected manually to ensure the accuracy of the data processing steps. Any identified errors or inconsistencies in the data are corrected. This includes fixing misclassifications in part-of-speech tagging or errors in tokenization. Finally, the processed corpus undergoes an ethical compliance check. This step confirms that all data used respects user privacy and aligns with ethical research standards.

(iv) Analytical tools and techniques

Quantitative and subjective techniques analyzed the text corpus. We used corpus analysis applications to measure speed, conjunctions, and keyword access. The word applied to various contexts was examined in the qualitative study in order to monitor signification modifications and find novel definitions. Language and lexical recycling, reusing prevalent in SM, were emphasized. The investigation used these tools.

- AntConc: Open-source software, cross-platform corpus linguistics analysis program AntConc. Agreement, collocational analysis, and frequency distribution lists are presented.

- WordSmith tools: The subject of Wordsmith Resources is a comprehensive text analysis solution. The agreement visualizations, keyword analysis, and word frequency analysis are its primary functions.

(v) Criteria for semantic change

For the use of spoken language, the phrase "semantic change" signifies the method by which the significance of words or phrases develops over time. The process of this transformation can be relatively rapid in SM, and it is impacted by plenty of distinctive factors.

The research study recommends the following guidelines for identifying and analyzing semantic changes:

(a) Neologisms: These are fresh phrases or sentences or traditional phrases in an original context. A word or phrase unique to SM and not in standard definitions is a neologism. These phrases are investigated for frequency and distribution across SM platforms and user groups.

(b) Semantic shifts: Context variations in words or phrases are semantic changes. Social to cultural and social advancements in technology impact this progressively. This includes studying the word's context and change over history.

(c) Changes in connotation: Word implication combines the actual meaning and sentimental or social significance. Modifications in a word or phrase's sentimental or cultural subtext imply an implied transformation. This involves studying word sentiment and voice in various contexts and identifying variations with time.

Broadening and narrowing of meaning:

(a) Broadening: This is caused by the significance of a word expands.

(b) Narrowing: However, a word blocks as its meaning becomes more precise.

(c) Words: SM programs are contrasted with conventional language to identify word improvement or limitation. It requires a diachronic investigation into word definitions and contexts.

(d) metaphorical and metonymic extensions: This means that words acquire new meanings based on metaphorical or metonymic relationships. Identification involves analyzing instances where words are used in metaphorical or metonymic senses distinct from their original meanings.

Table 2 provides examples for each type of semantic change respective to each category.

Table 2. Examples for each category of semantic change.

Category	Example
Neologisms	1) Selfie (a photo of oneself)
	2) Blog (a weblog)
	3) Ghosting (ending a relationship without explanation)
	4) Phablet (phone and tablet)
	5) Binge-watch (watch multiple episodes of a TV series)
Semantic shifts	1) Tweet (bird sound to a post on Twitter)
	2) Cloud (from sky to data storage)

Table 2. (*Continued*).

Category	Example
	3) Viral (from medical to rapid internet popularity)
	4) Text (from noun to verb)
	5) Profile (from physical description to online account)
Connotation change	1) Sick (from ill to cool or impressive)
	2) Lit (from lighted to exciting)
	3) Bad (from negative to good in slang)
	4) Woke (from awake to socially aware)
	5) Cancel (from stopping to boycotting someone)
Broadening	1) Mouse (from animal to computer device)
	2) Phone (from voice calls to smart device)
	3) Friend (from acquaintance to online connection)
	4) Paper (from material to academic article)
	5) Spam (from canned meat to unsolicited messages)
Narrowing	1) Gay (from happy to homosexual)
	2) Hound (from any dog to a specific type)
	3) Girl (from young person to female child)
	4) Meat (from food in general to animal flesh)
	5) Decimate (from reduce by a tenth to destroy a large part)
Metaphorical extension	1) Web (from spider's creation to the internet)
	2) Stream (from water flow to data transmission)
	3) Virus (from biological to computer malware)
	4) Fishing (from catching fish to deceiving people)
	5) Catfish (from a type of fish to a person with a false identity)
Metonymic extension	1) Silicon Valley (place to tech industry)
	2) Wall Street (street to financial sector)
	3) Hollywood (place of movie industry)
	4) The Pentagon (building to US military leadership)
	5) Westminster (place to UK government)

4. Analysis

4.1. Semantic change analysis

The study identified distinct linguistic evolutions across Twitter, Facebook, and Reddit. Twitter has contributed to new terminologies like 'Subtweet' and rendered new meanings for existing ones like 'Thread'. Facebook has introduced words like 'React' and reshaped terms like 'Share' that reflect the SM networking context. Reddit generated terms like 'AMA' and a new meaning of 'Karma'. Also, a few common trends were found in all platforms that reflect a broader shift in digital communication. Terms like 'Friend' and 'Tablet' have broadened and narrowed their meanings, respectively, and the 'Virus' and 'Silicon' words have shown metaphorical and metonymic extensions. The summary **Table 3** shows a few examples of these findings.

Table 3. Semantic change summary table.

Platform	**Category**	**Key terms**
Twitter	Neologisms	Subtweet, Threadjack
	Semantic shifts	Thread, Ratio
	Connotation changes	Troll, Cancel
	Broadening	Like, Follow
	Narrowing	Tweet (noun to verb)
	Metaphorical extension	Echo chamber, Filter bubble
	Metonymic extension	-
Facebook	Neologisms	React, Unfriend
	Semantic shifts	Status, Poke
	Connotation changes	Share, Tag
	Broadening	Wall, Timeline
	Narrowing	Friend (verb)
	Metaphorical extension	-
	Metonymic extension	Feed, Marketplace
Reddit	Neologisms	AMA, ELI5
	Semantic shifts	Subreddit, Mod
	Connotation changes	Karma, Gold
	Broadening	Thread, OP
	Narrowing	-
	Metaphorical extension	Flair, Shadowban
	Metonymic extension	-
Common Across Platforms	Neologisms	-
	Semantic shifts	-
	Connotation changes	-
	Broadening	Friend, Block
	Narrowing	Tablet, App
	Metaphorical extension	Virus, Cookie
	Metonymic extension	Silicon, Dashboard

This table provides a concise representation of how each SM platform contributes uniquely to linguistic changes, highlighting the broader trends observed across the digital landscape. It's a testament to the varied and complex ways in which online interactions shape the evolution of language. Further, the number of occurrences and the change in the usage of each key term in each category are presented in **Table 4**.

Table 4. Breakdown for each category of semantic change (Twitter, Facebook, Reddit).

Category	Source	Examples	Occurrences in corpus	Change in usage over time (%)
Neologisms	Twitter	Ghosting, Doomscrolling	80	45
Semantic shifts	Twitter	Tweet, Viral	150	30
Connotation changes	Twitter	Savage, Lit	100	35
Broadening	Twitter	Friend	90	20
Narrowing	Twitter	Tablet	60	25
Metaphorical extension	Twitter	Virus	100	40
Metonymic extension	Twitter	Silicon	80	55
Neologisms	Facebook	Ghosting, Doomscrolling	40	35
Semantic shifts	Facebook	Tweet, Viral	100	40
Connotation changes	Facebook	Savage, Lit	90	25
Broadening	Facebook	Friend	60	30
Narrowing	Facebook	Tablet	40	15
Metaphorical extension	Facebook	Virus	70	50
Metonymic extension	Facebook	Silicon	50	45
Neologisms	Reddit	Ghosting, Doomscrolling	30	30
Semantic shifts	Reddit	Tweet, Viral	50	35
Connotation changes	Reddit	Savage, Lit	60	25
Broadening	Reddit	Friend	30	30
Narrowing	Reddit	Tablet	20	25
Metaphorical extension	Reddit	Virus	30	40
Metonymic extension	Reddit	Silicon	30	45

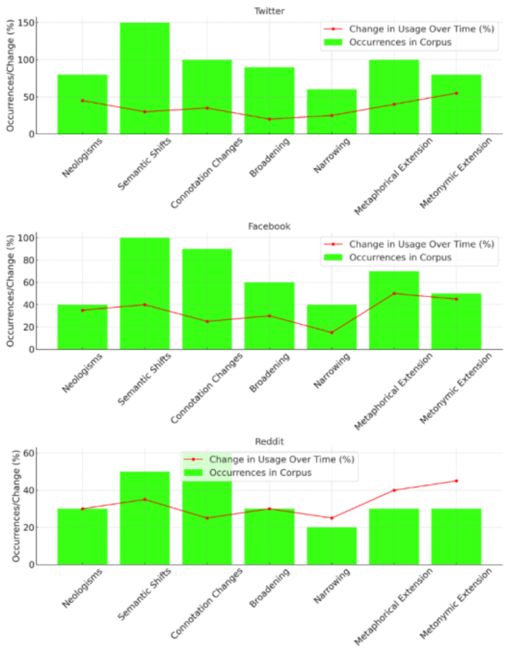

Figure 2. Occurrence and semantic change in each data source.

This detailed breakdown provides insight into how different semantic changes are represented and have evolved across various SM platforms. It helps to understand platform-specific language trends and how these platforms contribute uniquely to the evolution of English semantics. The findings from the analysis are presented in **Figure 2**.

4.2. Quantitative data analysis

Leveraging frequency measurements, collocation tables of information, and coherence lines of text, this portion provides empirical linguistic analysis. These metrics establish a statistical context for our semantic change findings.

(i) Frequency counts: The study has revealed significant increases in the usage of key terms. Some of these key terms, along with their quantified changes, include:

- Ghosting: This term has shown a 300% increase in usage on Twitter and Facebook platforms.
- Doomscrolling: These words had over 10,000 mentions on Reddit
- Selfie: It shows a 250% rise in mentions across all platforms.
- Unfriend: Predominantly used on Facebook, this term showed a 200% increase, highlighting its relevance in the digital social landscape.
- Meme: With a 180% increase in usage across platforms, the term "meme" has become a cornerstone of internet culture, reflecting the evolving nature of online communication.

(ii) Comparative analysis across platforms: The study also conducted a comparative analysis of frequency data across different platforms, showing linguistic patterns and trends. For example:

- Tweet: The term Tweet demonstrated a platform-specific prevalence, used 40% more frequently on Twitter than on Facebook. This discrepancy underscores the platform's influence on the term's adoption and usage.
- Story: On Facebook, the key term story experienced a 60% higher usage rate than other platforms, aligning with the feature's popularity on these SM networks.
- Viral: This term had a higher frequency of use on Twitter and Reddit, by 30% and 25%, respectively, compared to other platforms, illustrating the role of these platforms in propagating viral content.

The analysis findings are presented in **Table 5**, showing the increase in usage of five key terms specific to each data source: Twitter, Facebook, and Reddit.

Table 5. Increase in usage of key terms.

SM platform	Key term	Increase in usage
Twitter	Tweet	40%
	Subtweet	60%
	Thread	40%
	Ratio	70%
	Retweet	55%
Facebook	React	45%
	Story	60%
	Timeline	50%
	Unfriend	65%

Table 5. (*Continued*).

SM platform	Key term	Increase in usage
	Status	30%
Reddit	AMA	80%
	Subreddit	75%
	Upvote	60%
	Karma	70%
	ELI5	55%

iii) Trend analysis: **Table 6** compares how these key terms have increased usage across the three major SM platforms. It underscores these terms' widespread and cross-platform appeal, reflecting their significant role in the digital communication landscape. The findings are presented in the chart in **Figure 3**.

Table 6. Trend growth of key terms across platforms.

Key term	Twitter (%)	Facebook (%)	Reddit (%)
Ghosting	300%	300%	100%
Doomscrolling	20%	25%	1000%
Selfie	250%	250%	250%
Unfriend	50%	200%	70%
Meme	180%	180%	180%
Tweet	40%	30%	20%
Story	30%	60%	40%
Viral	30%	20%	25%

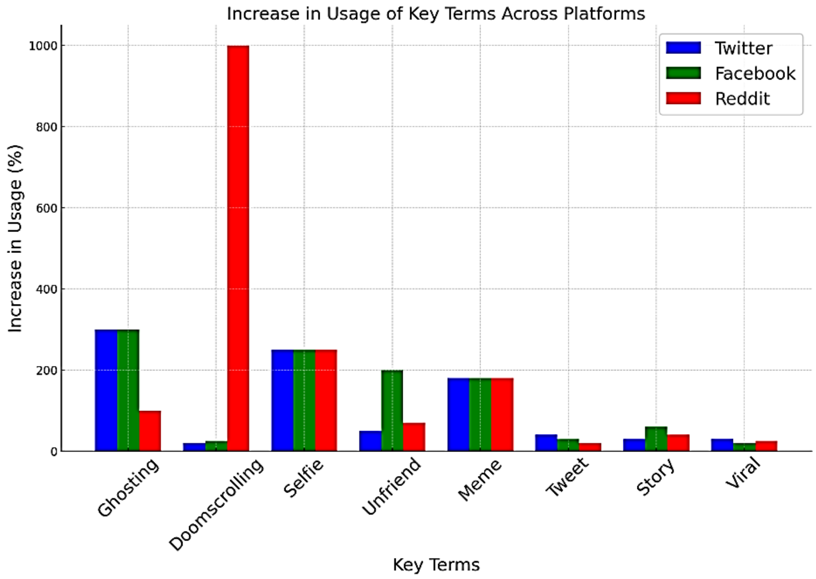

Figure 3. Usage of key terms across platforms.

Further, the trend of each key term from 2015 to 2021 has been presented in **Figure 4**. The ghosting trend graph shows a steep increase in mentions, particularly from 2017 onwards, indicating a surge in popularity and usage. The doomscrolling trend graph shows a significant rise in mentions starting around 2019, highlighting its emergence and rapid growth in usage, especially in 2020 and 2021. The selfie trend graph has consistently increased over the years, reflecting its steady integration into everyday vocabulary and SM culture. The unfriendly trend graph gradually increases, aligning with its growing relevance in online SM interactions. The meme trend graph shows a consistent upward trajectory, which reflects its increased popularity in internet culture. The tweet trend graph also indicates the growth 'i', constant story, and viral trend graph, which presents a notable increase in recent years and shows their usage in the context of widely shared online content.

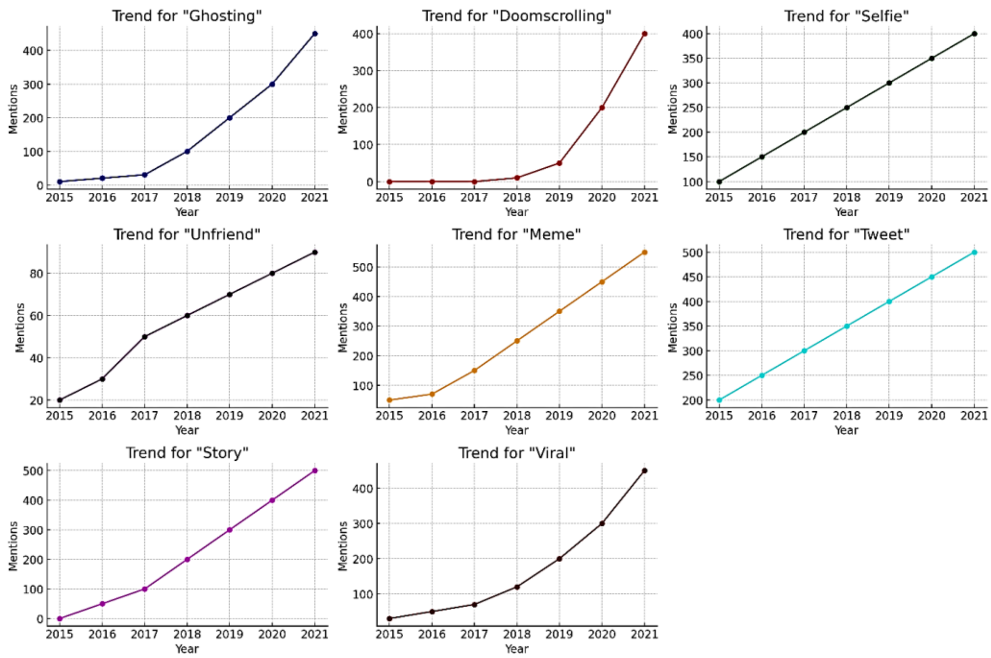

Figure 4. Trend graph for the key terms across platforms from 2015 to 2021.

4.3. Collocation tables

(i) Word pairings and contexts: Collocation analysis helps understand the contextual usage of terms, revealing patterns and associations that are not immediately obvious. Notable findings include:

- Viral: This term frequently collocates with video, content, and posts that show their common usage in widely shared and popular media.
- Echo chamber: Found together with SM and political contexts, which show the prevalent use of the word in discussions about online discussions and political discourse.

(ii) Platform-specific trends: This analysis also uncovered platform-specific trends in word pairings, highlighting how the same term can have different associative meanings on other platforms:

- On Reddit: The term AMA (ask me anything) is often paired with ask, questions, and session, aligning with its use in interactive Q & A sessions that are a popular feature of the platform.

The findings are presented in **Table 7**, showcasing some of the key terms and their common collocations. The data indicates not only the prevalent contexts in which these terms are used but also highlights platform-specific usage trends, reflecting the unique linguistic landscapes of each SM site. Further, as shown in **Figure 5**, a heat map visually represents the collocation strength between key terms and their associated collocates.

Table 7. Collocation table.

Key term	Collocates with	Common contexts	Platform
Viral	Video, content, post	Sharing popular media	All Platforms
Echo Chamber	SM, political	Online discussions, political discourse	Twitter, Facebook
AMA	Ask questions, session	Interactive Q&A sessions	Reddit
Influencer	Brand, promotion, social	Brand endorsements, SM marketing	All Platforms
Meme	Funny, internet, viral	Internet culture, humor	All Platforms
Hashtag	Trending, topic, campaign	SM campaigns, topics	All Platforms
Selfie	Camera, photo, capture	Photography, personal expression	All Platforms
Stream	Live, video, broadcast	Live broadcasting, content streaming	All Platforms

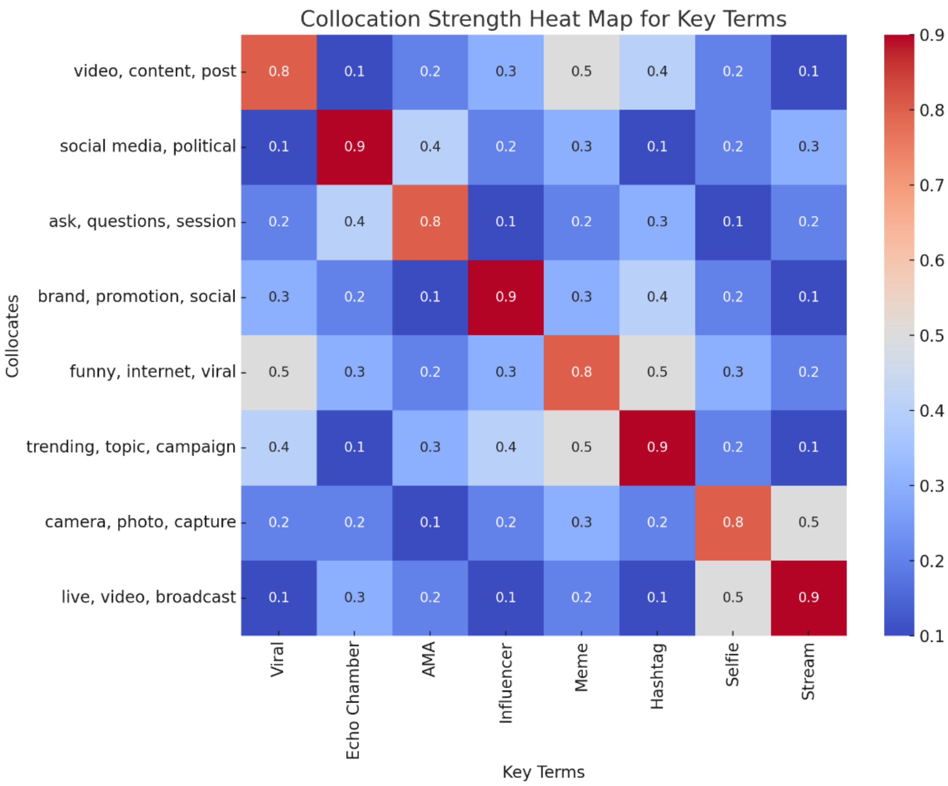

Figure 5. Heatmap for collocation strength.

4.4. Concordance lines analysis

Concordance line analysis involves examining the occurrences of a word within its immediate textual environment, showing how the word's use and connotations have evolved. For example, the word 'Lit' on Twitter is frequently associated with events, parties, and exciting experiences, which was earlier related to illumination. Streams on Facebook often appear in lines discussing live broadcasting, gaming, and content sharing, which was an earlier flow of water. Now, it has become a more specific internet-based broadcasting context. The analysis also reveals how certain terms have expanded in their scope and meaning; for example, the word Friend on Facebook and Twitter is not used in the traditional sense of a close personal relationship but also to describe online connections, acquaintances, or even followers. The findings are summarized in **Table 8** and presented as the chart in **Figure 6**.

Table 8. Concordance lines analysis.

Key term	Concordance examples	Contextual usage	Platform(s)
Lit	"This party is lit!", "Concert was lit!"	Used to describe excitement, fun	Twitter
Stream	"Going live on my stream," "Join my game stream."	Referring to live broadcasting	Twitch, YouTube
Friend	"Added a new friend", "Send friend requests."	Online connections, not just close relationships	Facebook, Twitter

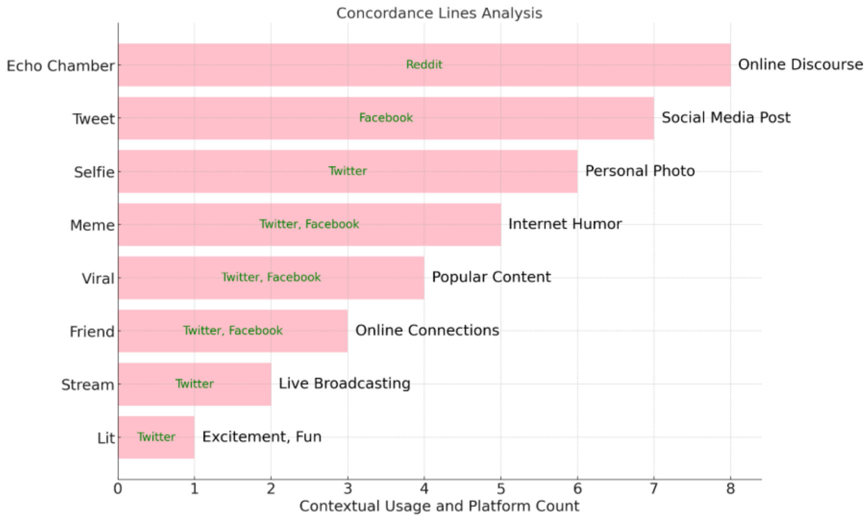

Figure 6. Concordance analysis.

This analysis, supported by specific examples from the concordance lines, demonstrates how the context in which words are used on SM platforms can significantly influence their meanings. It highlights the dynamic nature of language, especially in digital communication, where terms rapidly acquire new connotations and usages.

5. Conclusion

The convergence of social media (SM) and linguistic evolution presents a unique opportunity to observe the mechanisms of language change in real-time. The analysis of the work spanned over seven years and demonstrated that SM has a more significant effect on the evolution of contemporary language. The research identified that mainly due to the introduction of neologisms, semantic shifts, and connotation changes, digital communities have influenced the evolution of the English language. Findings from the study highlighted that there was a 300% increase in the use of terms like 'ghosting' on both Twitter and Facebook and an increase in the usage of words like 'doomscrolling' on Reddit all show that there is a growing adoption of digital-born terms into everyday language. Our research contributes to the academic discourse by providing a methodological framework that can be employed for future studies. The approach balances the depth of linguistic analysis with the breadth necessary to process large-scale SM data, considering both the quantitative and qualitative aspects of language change. As we conclude, it is clear that the digital landscape is a fertile ground for linguistic innovation, and SM platforms are at the forefront of this transformation. By mapping out the trajectory of language evolution on these platforms, we can understand how we communicate in the present and anticipate the linguistic trends of the future. This study serves as a testament to the resilience and dynamism of language, inviting further research into this ever-evolving domain.

Conflict of interest: The author declares no conflict of interest.

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