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LINGUISTIC PROFILING BASED ON SOCIAL MEDIA LANGUAGE: A REVIEW OF AGE DETECTION METHODS

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Abstract: This review explores recent advancements in linguistic profiling for age detection on social media. As digital communication becomes central to identity expression, researchers have developed models that infer users' age based on lexical, syntactic, and stylistic features. Studies across platforms like Twitter, Facebook, and Telegram show that linguistic variation often correlates with age. While machine learning approaches have shown promising accuracy, several limitations persist. These include overreliance on English-language corpora, insufficient representation of low-resource languages like Uzbek, and a lack of sociolinguistic theory integration. Ethical concerns, such as privacy and consent, are also underaddressed. This article categorizes existing methodologies, compares cross-cultural findings, and identifies contradictions in empirical results. It highlights the need for more inclusive, longitudinal, and ethically grounded approaches to age profiling. By outlining current gaps and future directions, this review contributes to the development of fair, transparent, and linguistically informed systems for age detection in digital contexts.

Keywords: Age detection, linguistic profiling, social media language, lexical features, syntactic complexity, machine learning models, multilingual NLP, cross-platform analysis, Uzbek digital discourse, forensic linguistics.

1.Introduction

In the digital age, language has become not only a medium of communication but also a rich source of information about the individual behind the text. Every message sent on social media-be it a tweet, a Facebook comment, or a Telegram chat-leaves behind linguistic traces that unconsciously reveal elements of a user's identity. Among the most studied of these identity features is age, a variable that has proven crucial for understanding generational shifts in digital discourse, as well as for applications in marketing, education, and cybersecurity. The notion that age can be inferred through language is not new. For decades, sociolinguists have explored how young and older people use different vocabulary, speech patterns, and pragmatic strategies in spoken communication. However, the transition to digital communication has changed the landscape. In computer-mediated environments, individuals adapt their linguistic choices to the speed, informality, and constraints of platforms like Twitter, Instagram, and Telegram. As such, a new field has emerged: linguistic profiling based on online language, in which researchers attempt to deduce characteristics such as age, gender, and personality using language as data. Linguistic profiling refers to the practice of analyzing language use to infer demographic or psychological attributes of the writer. When applied to age detection, linguistic profiling seeks to answer a fundamental question: Can we determine a social media user's age based on how they write? And if so, what linguistic features best signal age differences across generations? This question is more than theoretical. In practice, age detection plays a vital role in: Protecting minors from online threats, such as grooming and cyberbullying. Personalizing content, especially in digital marketing and targeted advertising. Providing insights in forensic linguistics, where anonymous social media content may need to be attributed to individuals based on age, gender, or region. Tracking

sociolinguistic change, as new generations bring new vocabulary, syntax, and communicative styles to digital platforms. The past two decades have seen a surge in research dedicated to automatic age detection, using both manual and computational approaches. Early studies focused on surface-level features such as vocabulary size, sentence length, and emoticon use. More recent works leverage machine learning, deep learning, and natural language processing (NLP) to classify users into age groups using thousands of linguistic variables. These models are trained on large corpora of age-labeled social media data and are evaluated for accuracy, interpretability, and cross-linguistic generalizability. Yet despite these advancements, the field faces several challenges:

Bias in training data: Most models are trained on English texts, especially from Western users, which may not generalize to users in Uzbekistan, Russia, or the Arab world. Lack of annotated corpora in low-resource languages like Uzbek or Kazakh makes supervised learning difficult.

Platform effects: User behavior differs across Telegram, Twitter, and Facebook, meaning that models built for one platform may not work well on another.

Ethical concerns: Automatically profiling users without their knowledge or consent raises privacy issues, especially in forensic or commercial settings.

Moreover, while many studies focus on the accuracy of age prediction, fewer examine why certain features are predictive, and how those features relate to broader sociolinguistic theories. Bridging this gap between computational methods and linguistic theory is essential if the field is to mature into a scientifically grounded and ethically responsible discipline.

This review article aims to provide a comprehensive synthesis of existing research on age detection through social media language. Specifically, it will:

Outline the methodology used to select and analyze relevant literature.

Summarize key linguistic features-lexical, syntactic, semantic, and stylistic-that correlate with age.

Compare computational approaches, including rule-based systems, machine learning models, and hybrid techniques.

Discuss findings from cross-linguistic and cross-platform studies.

Identify research gaps, including underexplored languages and demographic variables.

Offer suggestions for future research, especially on the integration of linguistic theory with AI models.

By reviewing studies from English, Russian, and Uzbek-language scholarship, this article aims to broaden the conversation beyond the Anglophone world and contribute to a more inclusive understanding of digital language variation across age groups.

2.Method of Literature Selection

In order to ensure a rigorous and comprehensive synthesis of research on age detection through linguistic profiling, this review employs a selective thematic literature review methodology. This approach prioritizes relevance, diversity, and scholarly rigor, allowing for both breadth and depth in identifying key findings across multiple disciplines, languages, and regions.

2.1 Research Databases and Sources

The literature reviewed in this article was drawn from a combination of global and regional academic databases, including:

Google Scholar (for multidisciplinary and open-access sources)

Scopus and Web of Science (for high-impact, peer-reviewed journals)

ResearchGate (for author-shared preprints and conference papers)

eLibrary.ru (for Russian-language publications)

Ziyonet.uz, and the National Scientific Portal of Uzbekistan (for Uzbek-language

academic articles and theses)

Search queries were formulated using Boolean operators and included combinations of the following terms: "age detection and social media language" "linguistic profiling and digital communication" "age prediction NLP" "возрастная лингвистика and интернет-коммуникация" "yosh guruhlarining tarmoq tili", "ijtimoiy tarmoqlarda yoshni aniqlash"

2.2 Inclusion and Exclusion Criteria

To maintain focus and relevance, studies were selected based on the following inclusion criteria:

- published between 2005 and 2024;
- addressed the linguistic characteristics of social media users with age as a variable
- focused on text-based analysis, rather than audio or video data;
- presented empirical findings, including computational models or qualitative linguistic insight;
- published in English, Russian, or Uzbek.

Exclusion criteria:

- studies that focused only on psychological or behavioral profiling without linguistic analysis;
- articles with anecdotal or non-peer-reviewed claims;
- non-academic blog posts or media reports.

2.3 Disciplinary Scope

The review spans multiple disciplines:

Sociolinguistics: Examining how age affects lexical and stylistic choices (e.g., Tagg, 2015; Androutsopoulos, 2006);

Forensic linguistics: Applying age profiling in legal and cybercrime contexts (Grant & MacLeod, 2020);

Computational linguistics and NLP: Modeling age through supervised learning (Nguyen et al., 2013; Rangel et al., 2015);

Digital communication: Exploring platform-specific language use and multimodal features (Zappavigna, 2012).

2.4 Language and Geographic Representation

This review consciously includes sources from diverse linguistic and cultural contexts. Of the 38 core publications analyzed: 22 were in English, representing the core of computational and forensic research 9 were in Russian, reflecting studies on age-related language use in post-Soviet digital spaces 7 were in Uzbek, offering emerging perspectives on local social media linguistics. Russian-language studies such as Chernysheva (2018) and Baranov (2019) provide detailed examinations of digital age markers, while Uzbek-language works like Jo'raev (2021) and Sobirova (2020) explore vocabulary, slang, and sentence structure across generations in Telegram and Facebook.

2.5 Limitations of the Literature Sample

While every effort was made to ensure balance, some limitations remain: Underrepresentation of non-Western computational studies, due to lack of accessible datasets or published results. Few multilingual comparison studies, especially involving low-resource languages like Uzbek. Potential publication bias, with more attention given to youth language than older adult digital discourse. Despite these gaps, the collected literature offers a sufficiently broad foundation for analyzing both theoretical trends and practical methods in age detection through linguistic profiling.

3.Review of Age Detection Methods

Age detection based on social media language is a rapidly evolving interdisciplinary field that combines computational linguistics, sociolinguistics, forensic linguistics, and artificial intelligence. Scholars and practitioners alike have sought to identify reliable

linguistic cues that correlate with a user's age group. This section reviews the major methodological approaches used in this area, grouped under four thematic categories: lexical and stylistic markers, syntactic features, machine learning and NLP-based models, and multilingual and cultural considerations.

3.1 Lexical and Stylistic Markers

One of the most salient differences in social media language across age groups lies in vocabulary choice and stylistic preferences. Younger users-especially teenagers and those under 30-tend to employ informal and creative linguistic forms such as:

Internet slang (e.g., "brb", "kek", "omg");

Abbreviations and acronyms (e.g., "idk", "tbh");

Phonetic spellings (e.g., "gonna", "luv", "wanna");

Elongated vowels and punctuational emphasis (e.g., "soooo happy!!!").

These stylistic tendencies are not merely superficial; they reflect identity construction, peer affiliation, and digital fluency (Eisenstein, 2013; Basile et al., 2022). In contrast, older users often exhibit more conservative lexical choices, preferring grammatically well-formed sentences, standard spelling, and less visual augmentation of text (Nguyen et al., 2011).

Nguyen et al. (2013), in a large-scale Twitter study, demonstrated that younger users employed significantly more expressive, abbreviated, and emotionally charged language than older users. This is echoed in Jo'raev's (2021) work, which found that Uzbek teenagers used more Russian borrowings and slang in Telegram messages, often combining native and foreign elements in creative hybrid forms. Similarly, Akmalova and Juraev (2022) highlighted that Uzbek youth often used a mixture of Russian, English, and native lexical forms depending on context and social group.

Stylistic features such as emoji frequency, emotive punctuation (e.g., "!!!", "???"), and code-switching have been successfully incorporated as features in supervised learning models with high predictive value (Rangel et al., 2015). Pavalanathan and Eisenstein (2015) further showed generational differences in emoji vs. emoticon usage, indicating that younger users are more inclined toward modern emoji use, while older users still use legacy emoticons like :-) or :-D.

Table 1 below provides a comparative overview of lexical and stylistic markers commonly associated with distinct age cohorts in digital communication.

Table 1: Age Group vs. Lexical-Stylistic Features

Age Group	Common Vocabulary	Emojis/Emoticons	Abbreviations	Style Examples
Teenagers (13–19)	Slang ("lit", "brb", "idk")	😭, 💀, 😂	"tbh", "fr fr"	Sheeesh! That was so cool 🔥
Young Adults (20–30)	Mix of slang and standard	😎, 🤔, 😊	"asap", "lol"	Not sure what's going on tbh.
Adults (31–50)	Standard vocabulary	🙂, 😐	Few abbreviations	I appreciate your response.
Older Adults (50+)	Formal language	Rare or none	Rare	Looking forward to hearing from you.

3.2 Syntactic and Sentence Structure Features

Syntactic complexity is another key marker of age in written digital communication. Young users, especially teens, frequently produce short, fragmented sentences, often lacking punctuation, capitalization, or traditional grammatical structure. For example:

"idk what to do anymore lol "

Such constructions reflect a prioritization of speed, emotion, and immediacy rather than linguistic precision (Crystal, 2008; Peterson, 2014). In contrast, older users often

produce more structured expressions such as:

"Today I visited the exhibition and found the experience deeply enriching."

These distinctions have been documented in blogging (Schler et al., 2006) and mobile messaging studies, where sentence length, punctuation use, and coherence were strongly correlated with age.

Common syntactic features used in age detection include:

- Average sentence length;
- Use of conjunctions and subordinators;
- Presence or absence of punctuation;
- Distribution of part-of-speech (POS) tags.

Baron (2008) argued that syntactic minimalism in youth digital writing is not indicative of language decline but a functional adaptation to mobile and social media norms. In morphologically rich languages like Uzbek and Russian, the syntactic profile of users shifts more drastically with age due to different exposures to formal writing norms.

3.3 Machine Learning and NLP-Based Approaches

The most significant advances in age detection have come from the integration of machine learning (ML) and natural language processing (NLP). These techniques allow researchers to train models on large-scale data, bypassing the limitations of manually designed rule sets.

Popular models and techniques include:

Traditional classifiers: Support Vector Machines (SVM), Na?ve Bayes, Decision Trees

Ensemble methods: Random Forests, XGBoost

Deep learning: RNNs, LSTMs, CNNs, Transformers (e.g., BERT)

Feature extraction: n-grams, TF-IDF, word embeddings (Word2Vec, GloVe), contextual embeddings (BERT, RoBERTa)

Rangel et al. (2015) reported that character n-grams and stylistic features (e.g., emoji use, orthographic stylization) had high predictive power in the PAN Author Profiling shared task. Deep learning models, particularly transformer-based models like BERT, have shown robust performance across languages and platforms (Liu & Xu, 2020; Wang et al., 2021).

However, one of the major limitations remains the lack of annotated corpora for low-resource and non-English languages (Tsvetkov et al., 2013). Most models are English-centric and often fail to generalize when applied to languages like Uzbek or Russian. Furthermore, age annotation is often missing from publicly available social media datasets, making supervised learning difficult without additional manual labeling efforts.

3.4 Multilingual and Cultural Considerations

Age-related linguistic variation is not universal but is influenced by cultural norms, educational practices, and societal values. For example, in collectivist cultures like Uzbekistan and Russia, even younger users might adhere to formal or respectful speech conventions online.

Baranov (2019) showed that older Russian users tend to favor classical grammatical structures and formal punctuation, while younger users are more expressive and experimental. Similarly, Abduazizova (2020) and Akmalova & Juraev (2022) noted that Uzbek youth, despite their use of slang and emoticons, still include polite forms and honorifics in chats with elders.

Platform-specific norms also affect linguistic behavior. Telegram encourages rapid, informal exchanges, whereas Facebook supports longer and more structured discourse (Mirkin & Mehler, 2020). As a result, models trained on one platform may not transfer well to others, necessitating platform-specific retraining and fine-tuning (Sidorov et

al., 2014).

Moreover, cross-lingual studies (Tsvetkov et al., 2013; Sidorov et al., 2014) have shown that linguistic markers of age can differ dramatically between languages, calling for localized model training and culturally aware annotation processes. Without such adaptation, predictive accuracy may be significantly reduced due to misinterpretation of language-specific markers.

4.Cross-Platform and Cross-Cultural Perspectives

While the majority of age detection research has focused on textual features and algorithmic models, increasing attention is being paid to the contextual factors that influence language use across different platforms and cultures. Language does not exist in a vacuum-platform design, user demographics, and cultural communication norms all significantly shape the way people express themselves online. These factors have direct implications for the accuracy, fairness, and generalizability of age detection systems.

4.1 Platform-Specific Language Behaviors

Different social media platforms encourage different modes of communication. These differences arise from technical constraints (e.g., character limits), affordances (e.g., availability of multimedia), and community norms. As a result, the linguistic behavior of the same user may vary significantly across platforms, affecting the reliability of age-related linguistic profiling.

Twitter: Character-limited, fast-paced, and public. Users tend to write short, abbreviated messages. Hashtags, acronyms, and emojis are common, especially among younger users.

Facebook: Supports longer posts and threaded discussions. Older adults are more prevalent on Facebook and often write in complete sentences, using formal or semi-formal language.

Telegram: Chat-based, often private or group-based. Users adapt a conversational tone, frequently omitting punctuation or capitalization. In Uzbek Telegram communities, youth commonly mix Uzbek with Russian or English slang (Jo'raev, 2021; Abduazizova, 2020).

TikTok & Instagram: More focused on visual content, but the captions and comments still provide linguistic data. Teenagers often use very brief, highly expressive language with emojis and slang, e.g., "lit ", "fr fr", "sheeesh!"

These platform-based linguistic variations pose challenges to models trained on a single-platform corpus, as the same age group may express themselves differently depending on the medium. For instance, a 16-year-old may use slang and memes on TikTok but write more respectfully in a school-related Facebook group. Without cross-platform data, models risk overfitting to platform-specific language.

To visualize these patterns more clearly, Table 2 compares typical linguistic behaviors by age group across four widely used platforms.

Table 2: Platform vs. Age-Related Language Use

Platform	Typical Age Demographics	Language Style	Common Features
Twitter	Teens, young adults	Short, slang-heavy	Hashtags, emojis, abbreviations
Facebook	Middle-aged, older adults	Longer, formal	Full sentences, punctuation
Telegram	All ages (varied)	Conversational	Code-switching, mixed language
TikTok	Teens	Expressive, emoji-rich	Emojis, Gen Z slang, memes

4.2 Cultural and Regional Language Variation

Age-based linguistic profiling is also deeply affected by cultural norms and regional language practices. What constitutes "youth language" in one country may not be the same in another, particularly in multilingual or diglossic societies. For example: In Western cultures, youth language often involves deliberate deviation from standard norms to signal individuality or rebellion (Eckert, 2000). In Uzbek or Russian-speaking societies, youth may still follow respectful linguistic conventions, particularly in addressing elders, due to cultural values rooted in collectivism and hierarchy. In Arabic-speaking regions, diglossia between Modern Standard Arabic and local dialects influences online expression, with younger users more likely to use dialects in informal chats. Moreover, code-switching is more prevalent in some linguistic environments than others. In Uzbekistan, Telegram users frequently switch between Uzbek and Russian, especially when using slang or quoting popular media (Abduazizova, 2020). This bilingual behavior complicates automatic classification, as lexical features may appear in multiple languages within a single utterance.

4.3 Dataset Bias and Model Transferability

Most age detection models are trained on English-language data, usually collected from Western platforms like Twitter or Facebook. These models, when applied to other contexts, often suffer from reduced accuracy due to differences in: Syntax and morphology (e.g., agglutinative structures in Uzbek), cultural norms affecting formality, address, and politeness strategie, Platform popularity and usage patterns across countries. For example, Baranov (2019) emphasizes that older Russian users favor longer, logically structured sentences, while younger users adopt Western-influenced styles with slang and emoticons. Rangel et al. (2015) also note that models trained in one language or region often fail to transfer effectively to others without substantial retraining or feature reengineering. Cross-cultural research is therefore essential not only for improving model generalizability but also for promoting fairness and inclusivity in linguistic AI applications. Neglecting regional variation can reinforce linguistic biases, leading to misclassification or discrimination, particularly in forensic or commercial contexts.

4.4 Toward Inclusive and Adaptable Models

The growing availability of multilingual datasets and advances in transfer learning offer promising solutions. Pretrained models such as multilingual BERT (mBERT) or XLM-RoBERTa can be fine-tuned on smaller regional datasets to improve performance in low-resource languages. Additionally, feature engineering should incorporate cultural variables such as honorifics, code-switching patterns, and digital literacy levels.

Some proposed strategies include: creating cross-platform corpora with age-labeled datafrom multiple platforms (Twitter, Facebook, Telegram), collecting localized lexicons of youth slang in non-Western languages. Including cultural pragmatics (e.g., expressions of politeness, kinship terms) in age classification features.By embedding these contextual insights into modeling efforts, we can build more robust, culturally-sensitive age detection systems that work across languages and communities.

5. Challenges and Contradictions in Age Detection Research

Despite considerable advancements in the linguistic profiling of age through social media data, several persistent challenges and contradictions continue to complicate both theoretical development and practical implementation. This section identifies four major areas of concern: data imbalance and representativeness, platform and language limitations, ethical dilemmas, and contradictory findings in the literature.

5.1 Data Imbalance and Representativeness

A core limitation in most age detection studies is the imbalance of age distribution in available datasets. Young users, especially those between 18 and 30, are overrepresented

in most social media corpora. In contrast, older age groups (50+) are significantly underrepresented, which skews model training and reduces generalizability. For example, Nguyen et al. (2013) acknowledge that the Twitter corpus used in their study contained a disproportionately large number of teenage and young adult users, making it difficult to distinguish between fine-grained age classes. Additionally, Rangel et al. (2015) note that performance on author profiling tasks drops considerably when trying to distinguish among middle-aged and elderly users due to data scarcity. Moreover, most datasets lack metadata consistency, including exact age, gender, or geographic location, which makes it difficult to assess the interaction of multiple demographic variables.

5.2 Platform and Language Constraints

As discussed in Section 4, most models are trained on English-language data from Western platforms like Twitter or Facebook. This raises two main issues:

1.Cross-linguistic transferability: Models trained on English often fail to perform well in other languages (Baranov, 2019; Abduazizova, 2020). Syntax, morphology, and pragmatics vary drastically across languages and influence age-related language features.

2.Platform-bound features: Youth language on Telegram or TikTok may differ significantly from that on Facebook. This complicates the creation of universal models and necessitates platform-specific adaptation. Additionally, low-resource languages like Uzbek suffer from a lack of publicly available corpora and NLP tools, severely restricting model development in these contexts.

5.3 Ethical and Privacy Considerations

Age detection systems operate in ethically sensitive areas. Inferring demographic characteristics without user consent raises significant privacy concerns, especially in forensic or marketing contexts. Crawford and Schultz (2014) argue that data-driven profiling-even with anonymized text-can still lead to surveillance, discrimination, or manipulation. In the context of youth, this becomes even more problematic. Children and teenagers are often unaware that their writing style can be used to predict personal attributes, including age. Moreover, the lack of transparent algorithmic decision-making makes it difficult for individuals to contest profiling results, leading to possible ethical violations in legal or educational settings.

5.4 Contradictions in Linguistic Findings

The literature shows conflicting results regarding which linguistic features are most predictive of age. Some studies emphasize lexical features (Nguyen et al., 2013), while others find syntactic complexity (Baranov, 2019) or stylistic markers (Rangel et al., 2015) to be more effective. Cultural differences further complicate interpretation. For instance: In some cultures, even teenagers may use formal sentence structures due to educational or familial expectations (Jo'raev, 2021). Meanwhile, some middle-aged users adopt youth slang to appear "modern" or to affiliate with younger audiences (Crystal, 2008). These contradictions suggest that age is not a purely linguistic construct, but one that interacts with social identity, context, and intentional performance.

6.Gaps in the Literature and Directions for Future Research

Despite significant advancements in age detection through linguistic profiling, the literature reveals several critical gaps that limit the field's theoretical robustness, methodological inclusivity, and practical applicability. Addressing these gaps is essential for building more accurate, ethical, and globally relevant models. This section identifies five primary areas requiring further exploration and offers specific recommendations for future research.

6.1 Underrepresentation of Non-Western Languages and Cultures

One of the most striking gaps in the current body of research is the linguistic and cultural bias toward English-speaking and Western users. Most age detection models are

developed using English corpora from platforms like Twitter, which do not represent the diversity of global online communication.

Languages such as Uzbek, Kazakh, Arabic, Swahili, and Indonesian-spoken by millions-are underrepresented or entirely absent from major computational corpora. Even in multilingual nations, regional dialects and youth varieties are often overlooked.

Future direction: Develop and share open-access corpora from underrepresented languages with labeled age data. Collaborate with local institutions to ensure culturally informed annotations and lexicon development.

6.2 Lack of Fine-Grained Age Categorization

Many existing studies group users into broad age categories such as <18, 18-30, 30-50, and 50+, which overlook important intra-group variation. The language of a 13-year-old differs significantly from that of a 17-year-old, yet both are typically categorized as "teenagers." Similarly, the linguistic behavior of a 31-year-old may differ from that of a 49-year-old, despite being grouped together.

Coarse categorization reduces the granularity of analysis and weakens the predictive power of profiling models.

Future direction: Adopt finer-grained age brackets (e.g., 13-15, 16-18, 19-22, etc.) in both annotation and analysis. This will allow for more nuanced profiling and better training of ML models.

6.3 Insufficient Integration of Sociolinguistic Theory

While many computational models report high accuracy, they often lack a theoretical grounding in linguistics. Linguistic markers are frequently treated as statistical features without exploring their sociocultural or psychological significance. As a result, models may perform well numerically but fail to explain why certain language patterns correlate with age.

Future direction: Encourage interdisciplinary collaboration between computational scientists and sociolinguists to incorporate concepts such as language accommodation theory, identity construction, and language change across the lifespan.

6.4 Scarcity of Longitudinal and Multimodal Studies

Most studies analyze static corpora collected at a single point in time. This limits our understanding of how individuals' language evolves with age or in response to life events, platform changes, or social influences.

Similarly, the focus remains overwhelmingly on textual features, while images, memes, audio messages, and video captions-which are common in platforms like TikTok or Instagram-are often ignored.

Future direction: Conduct longitudinal studies that track language use over time across age groups. Expand research to multimodal analysis to capture the full spectrum of digital communication.

6.5 Ethical Frameworks Are Underdeveloped

The ethical implications of age detection, particularly concerning privacy, surveillance, and consent, are insufficiently addressed in most technical papers. As profiling tools become more sophisticated, the risk of misuse-such as unauthorized surveillance, targeted advertising, or algorithmic discrimination-grows.

Future direction: Establish ethical guidelines for the development and deployment of linguistic profiling tools. These should include transparency protocols, user consent mechanisms, and audit trails for algorithmic decisions.

In summary, the existing literature on age detection in social media language reveals several notable gaps that require scholarly attention.

First, there is a significant lack of linguistic diversity, as the majority of studies rely on English-language corpora. This leads to the underrepresentation of low-resource languages

such as Uzbek, and highlights the need for building datasets in a wider range of languages.

Second, many studies apply coarse age groupings, such as combining all individuals aged 30-50 into a single category. This approach conceals meaningful differences within those age ranges. Therefore, more refined age categorization is necessary to improve the precision of age profiling models.

Third, computational approaches often lack theoretical grounding from sociolinguistics. While machine learning models extract statistical patterns from data, they rarely engage with sociolinguistic concepts that explain why certain linguistic features are age-related. Future work should integrate theoretical insights to provide more context-aware interpretations.

Fourth, the literature lacks longitudinal studies, which means researchers are unable to track how individual language use changes with age or over time. Additionally, most research focuses exclusively on textual data, ignoring multimodal elements such as images, memes, and voice messages. These should be incorporated to reflect the full nature of digital communication.

Fifth, ethical considerations are frequently overlooked. Many models are built and deployed without clear consent, transparency, or privacy frameworks, raising concerns about potential misuse, especially in forensic or commercial applications.

In light of these gaps, future research should prioritize more inclusive, fine-grained, theoretically informed, ethically sound, and longitudinal approaches to age detection in digital communication.

7.Conclusion

The field of age detection through linguistic profiling on social media has witnessed significant growth over the past decade, fueled by advances in computational linguistics, sociolinguistics, and machine learning. This review article has examined key approaches, findings, and challenges in the identification of users' age groups based on their written digital communication.

The analysis shows that age-related linguistic variation manifests in diverse ways, including lexical choice, syntactic complexity, stylistic features, and multimodal behaviors. Younger users typically exhibit informal, emotive, and abbreviation-rich language, whereas older users tend toward more formal and grammatically structured expression. These distinctions are observable across platforms such as Twitter, Facebook, and Telegram, although their expression is shaped by platform affordances, community norms, and cultural contexts.

Moreover, machine learning techniques-ranging from traditional classifiers to deep learning models-have demonstrated promising accuracy in age prediction tasks. However, these technical advances are not without limitations. Many models rely on English-language datasets, overlook theoretical grounding in sociolinguistics, and fail to account for regional, cultural, and platform-specific nuances. In addition, ethical and privacy concerns regarding the automated profiling of users remain insufficiently addressed.

This review identifies critical gaps in the literature: the underrepresentation of non-Western languages, insufficient granularity in age categorization, lack of longitudinal studies, limited multimodal research, and the absence of robust ethical frameworks. These limitations hinder the development of universally applicable, transparent, and fair age detection systems.

Future research must adopt amore inclusive and interdisciplinary approach, combining computational power with linguistic theory, ethical design principles, and cultural sensitivity. By doing so, scholars and developers can build tools that not only improve the accuracy of age detection, but also respect the diversity and dignity of users in digital

spaces.

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