A comparative study of English lexical variations based on gender on social networks: from 2015 Twitter to 2025 Twitter (x)

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Abstract
This study explores and compares lexical variations on Twitter and X (formerly Twitter) as social networks, based on gender and gender homophily. Data were collected at ten-year intervals from the same platform. The first dataset was collected in 2015, with 400 tweets (200 female, 200 male) randomly selected using Wamp Server. Gender classification was confirmed manually and via test data. Tweets were analysed through categories adapted from Bamman (2014), including named entities, taboo and swear words, numbers, emotional terms, emoticons, kinship terms, abbreviations, hashtags, and pronounceable/non-pronounceable words, along with emerging categories such as political and romantic words. Frequencies were examined, and clusters were formed based on lexical similarity to analyse language independent of gender stereotypes. Gender homophily was investigated by examining the gender composition of twenty networks using binomial distribution. In 2025, data were recollected; due to restricted access, 200 tweets were manually compiled. Findings suggest that language use may be gendered within the dataset; however, digital language differs from real-life use. Female authors tended to use more political, emotional, and interactional language, while male authors used more romantic expressions. Female tweets also included more swear and taboo words, as well as more hashtags. Male networks exhibited gender homophily, whereas female networks did not. When 2015 and 2025 data were compared, several patterns reversed, particularly in hashtags and romantic words, with increased use by male and female authors respectively. Political words showed a more balanced distribution. Gender homophily patterns also shifted, with no clear evidence of homophily in 2025.

***Keywords**: Twitter, X, gender, lexical variations, gender, homophily, digital/virtual environment, sociolinguistics*

Introduction

Since online social networks have grown rapidly in recent years and they have turned out to be a part of majority of people's daily lives, there is a substantial body of research on the use of language on them (Argamon, et al., 2007; Pedersan & Macafee, 2007; Kunsmann, 2013) and such studies have become subjects for sociolinguistics today. One of the most interesting sides of social networks is that they provide a common platform for their participants where they enable customization, sharing and communication in any aspect. On the other hand, social networks seem to provide a plenty of language data, as they create a community in which it is even possible to witness the communication of people who have never met or have known each other for years without meeting in person. As being one of these social networks, 'Twitter' provides significant data on language use. As such, based on Twitter Statistics (Post, 2010) Twitter alone had 645.750.000 global users and 289.000.000 of them were active users in 2015 which is around 368 million today for Twitter (X) platform. The number of tweets per each second is about 9.100 as Cohen and Ruths (2015) claimed. Many studies in sociology, linguistics and sociolinguistics today focused on

Twitter (X) because of its widespread services and the facility of letting its users to keep their accounts and sharing in public.

Twitter (X) alone has already been a community and as Kwak et al. (2010: 591) claimed:

> Common practice of responding to a tweet has evolved into well-defined mark-up culture: 'RT' stands for retweet, '@' followed by a user identifier address the user, and '#' followed by a word represents hashtag. This well-defined mark-up vocabulary combined with a strict limit of 140 characters per posting conveniences users to spread information.

As being different from other social media networks, Twitter (X) does not reveal latent features of users such as age, gender and ethnicity. That is, it provides a comprehensive database to study on how language conveys personal attributes including gender.

As Holmes (1997) stated, gender is more salient than social class. Based on some studies in relevant literature (Haas, 1979; Crawford, 1995), male and female use of language differs; however, it is not simple to draw up gender boundaries, particularly, in social media context. West and Zimmerman (1987: 13) claimed that doing gender involves "complex socially guided perceptual, interactional, and micro-political activities". There might be many reasons for these differences including women's subordinate social status, male-dominated patriarchal societies, insecure situation of women in society, learned social codes as explained by Kunsmann (2013: 2) in the following quote:

> Lakoff observed that women's use of color terms *(mauve, ecru, lavender*), of adjectives (*divine, adorable*), their frequent use of tag questions (*John is here, isn't he?)* and weak expletives differed radically from male use. Taking her cue from Bernstein (1972) theory of language codes she claimed that women's linguistic behavior is deficient when constructed with male speech behavior. As one explanation for this deficiency she pointed to the differences in the socialization of men and women.

Similarly, Fishman (1978; 1983) portrayed women as ''shift workers of routine interaction'' (p. 99). In his studies, Fishman (1978, 1983) claimed that men govern the talks as women is always in need of ensuring responses. Although there are some later studies (i.e. Nichols, 1983; Graddol and Swann 1989; Freed 1996) which criticized Fishman (1978; 1983) and Lakoff (1975), it is seen that women/ feminine speech has been described as a powerless, fragile, clumsy and even a symbol of weakness. This was described by male dominance in society and pre-existing patterns of this hierarchy which may lead a similar communication style online, as well, by such researchers. Although there are controversial ideas on online conversations as being ungendered/ asexual, Pedersen and Macfee (2007) claimed that there were early suggestions regarding that online communications were 'gender-blind' and they were democratic platforms that provided equal facilitates to everyone regardless of being male or female. On the other hand, some others suggested that online platforms do not neutralize gender, but the male dominance continued in online communities. According to Herring (1996) women and men have different online styles,

> …with the male-gendered style being more adversarial, including strong assertions, self-promotion, lengthy post, put-downs, and sarcasm aimed at others. In contrast, the female gendered-style was characterized by supportiveness and attenuation, including appreciation and community-based activities, thanks, apologies, and questions (p. 1473).

As it seems, the linguistic diversity was mostly based on the stereotype of 'masculine' and 'feminine'. However, it is not easy to suggest that 'masculine' sentences have some certain dimensions while 'feminine' sentences have those others. If gender in linguistics was interpreted as 'masculine' and 'feminine' way of speaking, we might claim that it limits the large scaled area of linguistics and undervalued it to a 'two' dimensional stereotype. In turn, it may not be the gender that assigns the language but based on the stereotypes it may be the language who assigns gender. It was also said that, during the 60s and 70s, many feminists accepted that biological differences were used in many societies just to engender male/ female distinctions. From this perspective, as Holmes (1997: 199) claimed, "women's identity is signaled not so much by the choice of particular linguistic variants which contrast with those preferred by men, but rather by the ways in which women are often required to use language to construct a much wider range of social identities" and Holmes added that "those identities express a wider range of social roles than men.''

Today, it is possible to say that these established gender stereotypes are also moved to social media contexts such as Twitter. The Twitter is likely to provide more freedom when compared to the social codes that are enforced by our neighborhood, or it is possible to say that Twitter offers a completely different linguistic variety that can be free from gender stereotypes.

Gender, language and social media

There are many opinions on the gender-social media relations such as Tannen's (1993: 7) arguing that "…differences between women's and men's conversational stories reflect and create women's and men's divergent worlds." Similarly, Johnstone (1993: 7, cited in Tannen, 1993) indicates that "…women's talk involves social power through community while men's talk involve power that comes from individuals themselves. Men had details about places, times and other things; women mostly talked about people."

The relevant literature (Haas, 1979; Crawford, 1995; Herring 1993, 1996; Holmes 1997; Pederson, et al., 2007; Kunsmann, 2013; Bamman et al., 2014) indicates that language is gendered in society and gendered language is on social media today; however, social media have their own environment by offering their authors both more freedom and restriction; more interaction and less communication; more latency and less privacy; even different codes and rules. As such, social media can have their own language as being different from the language in society. As it can be seen in relevant research, language is mostly gendered because of social codes, tenets and disciplines that construct and shape people with different sexes. Then it can be asked whether social media with their own tenets and creeds lead gendered talk.

The literature on media and gender studies has validated that social media have had gendered language and maintained the existing stereotypes about female and male language even on social media (Pederson, & Macafee, 2007; Bamman et al., 2014).

While early studies on gender and language have often relied on binary distinctions between "male" and "female" speech styles (e.g., Lakoff, 1975; Tannen, 1993), contemporary sociolinguistic research increasingly conceptualizes gender as a socially constructed and performative phenomenon rather than a fixed biological category. Drawing on Judith Butler's (1990) notion of performativity, gender is understood as something that is enacted through discourse and interaction rather than inherently possessed.

In addition, recent approaches emphasize intersectionality, recognizing that gender interacts with other identity dimensions such as culture, class, and digital participation practices. This perspective challenges earlier essentialist assumptions that associate specific linguistic features rigidly with male or female speakers.

Despite these developments, empirical research on large-scale social media datasets often remains constrained by the available metadata, which typically encodes gender in binary terms. Therefore, while acknowledging the limitations of binary categorization, the present study adopts a binary operationalization of gender due to methodological constraints inherent in Twitter (X) data. This approach allows for comparability with earlier studies while recognizing that gender identities in digital environments are more fluid and complex than this classification suggests.

Lexical markers of social media

Linguistic variations based on gender have revealed different dimensions so far, as research has shown. For instance, Bamman, et al. (2014) mentioned some of them; firstly, it is expected that female-authored discourse is likely to be more extensive by lengthening, such as, 'yesss' or 'nooo'. Additionally, non-standard spelling and abbreviations were projected as female style while masculine language is portrayed as having tendency to use proper nouns, more quantifiers and more swear and taboo words.

Female-authored discourse has also been described with the words regarding family, society, and kinship while men language has had more words related to finance and money. (Elekaei et al., 2014). Also, words related to the sport have always been attributed to men language. All these classifications in related literature have common ideas regarding fragility of female-authored discourse that is equipped with sensitivity and emotions while male-authored discourse is representing directness, less sensitivity and oriented with money, sports, and technology words mostly. Additionally, based on the related literature again, male and female language may even differ in use of preposition, timing adverbs, places, number of words, and the choice of grammar (Elekaei et al., 2014).

Gender homophily and social media

Bakshy et al. (2012: 1) defined homophily as ‘‘the tendency of individuals with similar characteristics to associate with one another.’’ People are most likely to interact to whom they are similar, and it is possible that they influence each other. Bisgin et al. (2010) stated that homophily was categorized into two, such as status homophily and value homophily. Status homophily is related to social status while value homophily is pertinent to individuals who are similar and think alive.

Regarding Twitter, people express their own opinions and attributes that lead the possibility of homophily; on the other hand, it is not easy to decide on homophily on a virtual world as it involves many dimensions such as age, education, social status and gender. Homophily is applicable to gender variations, as well. It might be possible that people interact with same genders on social media. Bamman et al. (2014) collected corpus data from Twitter and checked them for homophily. The results indicated that 63 % mutual corrections were the same gendered. The idea of homophily is based on ‘‘the birds of a feather flock together.’’ (Bamman et al., 2014: 149).

Recent research has expanded the understanding of homophily in digital environments by integrating computational and network-based perspectives. Studies demonstrate that homophily and social influence jointly shape information diffusion processes, highlighting the importance of modelling both relational dynamics and structural network properties in social media contexts (Shang et al., 2022). Moreover, homophily is not a uniform phenomenon but varies across different social scales, with stronger similarity patterns observed in close-knit groups and more heterogeneous interactions across broader networks (Rizi et al., 2025).

Empirical research on social media interactions further reveals that homophily is shaped by multiple intersecting factors, including gender, political affiliation, and institutional context. For instance, analyses of Twitter (X) interactions among political candidates show that while homophily is widespread, gendered patterns differ in how these connections are formed, with women and men exhibiting distinct interaction strategies (Ciroianu & Coffé, 2025). In addition, recent surveys in social network analysis emphasize that homophily operates through both status-based and value-based similarities, playing a key role in the formation of online communities and the emergence of information clusters and echo chambers (Khanam et al., 2022).

These developments suggest that homophily in digital environments is a dynamic and multi-layered phenomenon, shaped by both structural network properties and context-dependent user behaviors.

Related literature

Recent advances in technology have led a growing body of research on social media, Twitter (Burger et al., 2011; Bamman et al., 2014). In turn, the variation of linguistic characteristics according to the author’s gender has become doable in corpus in addition to the numerous studies that have been conducted to investigate gendered-language relation and lexical variations on social media.

Aiseng (2025) conducted a study to examine language ideologies in the context of South African Twitter (X) discourse by compiling a corpus of South African Twitter (X) data and aimed to exemplify how language ideologies of the community in this context display a tendency towards colonial principles of hierarchy, power and superiority. The study findings emphasized the importance of multilingual and multicultural digital spaces to negotiate the identities of users by utilizing language resources.

Recent empirical studies have further examined gendered language use in social media environments through large-scale and cross-platform analyses. Arshad et al. (2022), analyzing Facebook discourse within a feminist stylistic framework, found that male users tend to employ more assertive and publicly oriented language, whereas female users adopt more relational, polite, and solidarity-oriented expressions.

Similarly, Romadloni and Sari (2025), in their analysis of a large corpus of tweets on X (formerly Twitter), reported that female users tend to produce shorter, more emotionally expressive and relationship-focused content, while male users more frequently generate longer and action-oriented messages. However, their findings also indicate that such differences are not always statistically robust, highlighting the role of contextual and interactional factors in shaping digital communication.

In addition, Elmahdi et al. (2024) demonstrated that gendered communication patterns observed in face-to-face contexts are partially maintained in online environments, where women tend to use more supportive and emotionally expressive language, whereas men are more likely to adopt authoritative and opinion-oriented styles.

These findings suggest that gendered linguistic patterns persist in digital communication; however, they are dynamically shaped by platform-specific affordances and user practices rather than being fixed or universal. Building on these recent findings, earlier computational and corpus-based studies have also explored gendered linguistic variation in online environments using different methodological approaches.

Ikea and Savoy (2022) aimed to analyze ten machine learning strategies to define stylistic variances between genders on web-based communications, particularly tweets on Twitter. The study employed CLEF-PAN to extract corpora and provided an answer whether it is easy to identify terms related to gender as positive. The study confirms male style is more frequent with numbers and determiners and unlike previous studies appear to use negations and personal pronouns of third person. Also, female authors' tweets are rich in prepositions, personal pronouns, punctuation symbols and emojis.

While Ikea and Savoy (2022) focused on the stylistic variances, Bahammam (2018) was inspired by the growing popularity of Twitter-hash tagged debates in Saudi among men and women on woman rights by employing an eclectic qualitative method with a ore sociolinguistic focus. The study compiled a corpus of 1000 text-based tweets on two-selected topical hashtags which are on woman's travelling and marital status. The study findings are important to reveal that in a discourse privileging man over women, digital space offers meso-discursive strategies such as "referential and predicational", "assimilation and differentiation", "intensification and mitigation", laughter, emoticons, mocking, and humor and reflects a gradual social change in Saudi society by providing a space for public deliberation of social practices relating woman and the power of transformative potential of Twitter.

A similar study was conducted by Bamman et al. (2014) to investigate the relationship between gender, linguistics style and social networks by using a corpus of 14.000 Twitter authors. Twitter users were clustered based on their linguistic similarity; however, clusters were also gender oriented. For each cluster, it was examined whether authors' language matches the classifier's model for gender assignment and social network homophily was also examined. The results indicated that most of the clusters revealed strong gender orientations. Females and males showed a distinction between topic and style. Women used fewer dictionary words, significantly fewer abbreviations and emoticons as being different from previous study conducted by Dunn (1961). Male-dominated clusters had more dictionary words and pronounceable non-standard words, whereas taboo words were preferred by men in accordance with Dunn (1961). Regarding homophily, the results indicated that an average woman in the dataset have gender composition of 58 % of female and 67 % of male for male users. As the proportion of same –gender increased, the same-gender markers increased, as well.

As regards classifying gender and examining gender recognition on social media by linguistic variations, Halteren and Speersta (2014) conducted a similar study on Dutch tweets by collecting data from 600 users during 2011 and 2012. Tweets were examined to distinguish female and male authors based on purely lexical features in unigrams (single tokens), bigrams (two adjacent tokens), trigrams (three adjacent tokens) and bigrams (two tokens without adjacent). The study recruited Principal Component Analysis (PCA) for classification. All text samples were tokenized, and unigram tokens dominated the data to present best features. Regarding analysis, how often the token is used by each gender was taken into consideration and the percentage of the authors in the corpus data was measured to see whether they are in agreement with the true gender. Overall, the results portrayed female authors in a very emotional place and exemplified with 'omg', giggling, emotionally loaded adjectives such as 'nice', 'sweet' while men side was portrayed rather differently with many location adverbs, football-related words, playing, winning, losing. Additionally, female author tweets were claimed to have more intensified adverbs with adjectives such as 'so tired', 'so happy' while male tweets were illustrated as having pragmatic endings such as 'good, man'.

Actually, all studies above confirmed the variance in females' and males' use of language and they all characterized female language as free from taboo and swear words, endowed with emotionally full adjectives, emojis, prepositions and punctuation symbols while male-authored discourse was described as full with sports, games, dictionary words, numbers (Ikae & Savoy, 2022), pragmatic and handy phrases. That is to say, literature reflects the socially coded and portrayed fragile female stereotypes in contrast to men's powerful and tough language style. Regarding gender, it is really difficult to interpret the literature gender-blind and it is unfortunate that gender studies may already have gender subjectivity in itself. Similar results were presented by Pedersen and Macafee' study (2007: 1491) which was conducted to examine gender differences in blogging and the findings suggest that women have a lower profile in blogging as they have more "fear from online stalkers'' and Arnold and Miller (2000) stated that "academic women are inhibited online because their vulnerability as women remains part their persona as academics." (as cited in Pedersen and Macafee, 2007: 1491).

In addition to these, some other studies were conducted to examine gender homophily on social media. Zamal et al. (2012) conducted a study in Canada by considering three attributes which are gender, age and affiliation. The data were collected from Twitter; 200 tweets with one label (e.g. female or male) were studied. The tweets were investigated based on k-top words, k-top stems, k-top diagrams and trigrams, k-top co-stems, k-top hashtags, frequency statistics, retweeting tendency and neighborhood size. The data were analyzed with a 10-fold cross-validation. All friends of a Twitter user were included in the study to assess homophily. The closest friends were decided based on retweeting and mentioning at most times. The results indicated that neighborhood features are enough to get good accuracy which indicated homophily on Twitter.

A similar study was conducted by Choudhury et al. (2010) to investigate the impact of user homophily in online social media. The data were collected from Twitter and the results demonstrated homophilous inclination that may lead information diffusion on a given topic. Mostly, homophily explained the diffusion in the data and trends were measured as ~15-25%.

In contrast to above studies, Bisgin et al. (2010) investigated homophily on social media by collecting data three representative social media sites; blog catalogue, last.fm and live journal. The overlapping interests and community structure were examined by identifying the communities in each social media site and figuring out the interests. Results of the study indicated that the influence is not a strong factor for building new ties; in other words, connections are not based on common interests at all. In the context of online social media, close friends may differ in preferences.

The studies above showed that there is a plenty of research in the relevant literature about language use on social media networks and gender variations. The results of almost all studies showed congruity that language on Twitter is gendered; however, none of these studies indicated a difference from stereotypical lexicon of female and male users. Female social media users had an emotional style, intimacy while male authors had more taboo, finance, sport and money related words and indicate a senseless language (Bamman et al., 2014; Halteren & Speersta, 2014). In that, social media has been improving so fast that literature should be able to follow this change and its effects on language. On that point, literature seemed to be in need of new aspects and interpretations regardless of suggested stereotypes and a new frame which would be able to explicate the new virtual society's language.

Research focus and aim

This study aimed to scrutinize lexical variations on Twitter and Twitter (X) as a social media network regarding gender and explore the existence of gender homophily on Twitter author's and Twitter (X) authors' network connections by comparing the data from 2015 to 2025 It is designed to answer following questions:

Research questions;

1) Do users' tweets show variances in their language use based on gender on social media Twitter and Twitter (X)? How?
2) Do users' tweets show variances in their language use based on gender from 2015 to 2025 data on social media Twitter and Twitter (X)?
3) Does gender composition of an author have any effects on classifier's assigning gender on the text beyond the gendered language itself? What and how?
4) Do users' tweets with a greater proportion of same-gender ties make gender use of gender-marked variables in social media? How?

Method

The study employed a quasi-longitudinal comparative design to explore and compare the lexical variations in Twitter context based on gender by collecting data twice, ten years apart from 2015 to 2025. The term quasi-longitudinal is used because although the data were collected ten years apart from the same platform, identical data extraction conditions could not be maintained due to major changes in platform accessibility and technical affordances over time. This design enabled a structured comparison of linguistic patterns across two temporally distant datasets while also acknowledging the methodological constraints of changing digital infrastructures.

Relevant research in the field has already included several studies regarding this topic; however, the results are mostly concorded with the real language in society and most studies have examined the data based on stereotypical codes of gendered language of society.

Tweets

The data were collected from Twitter in 2015 and from Twitter (X) in 2025. Twitter/X was selected because it is a public-facing social media platform that provides a substantial amount of naturally occurring written discourse across a wide range of users, topics, and interactional styles.

The study was conducted in virtual context and users' tweets were chosen randomly with the help of a Wamp Server that helps to download the most recent tweets. 400 Twitter authors' tweets were studied; 200 of them were female and 200 were male. The authors' names or anything about their identities were not used or shown in the study even if they do not use their real names on Twitter. Their privacy was given importance for ethical concerns. Gender classification of Twitter authors was confirmed by checking manually and through via test-data. Tweets of authors were studied based on ten categories adapted from Bamman (2014); *named entities, taboo words, swear words, numbers, emotion terms, emoticons, kinship* *terms, abbreviations, hashtags, pronounceable and non-pronounceable dictionary words* and two more emerging themes*; political and romantic words.* The study investigated the data collected from users' tweets in two ways; at first, categories were formed, and the data were divided into two as female and male tweets regarding gender. Secondly, the data were divided into clusters based on the use of similar words regardless of gender and they were studied twice to see whether gender skew and language use showed parallelism. It is important as the data were examined free of any gendered categories at second time. Additionally, it is aimed to investigate gender homophily as Twitter has been a new community that may present invaluable data regarding the use of language of its users and behaviors. Twitter may have acted as a representative of society as having many people with different backgrounds that may not be possible to access in real world.

Data collection

In this study data was collected at two different time points with comparable procedures in the same way, ten years apart, the first in 2015 and the second in 2025. Although the study was designed as a longitudinal comparison between 2015 and 2025 datasets, it is important to note that data collection procedures differed due to changes in platform accessibility and technical constraints. In 2015, tweets were collected via API-based tools (Wamp Server), whereas in 2025, data were collected manually due to restricted access to automated extraction tools. To mitigate potential inconsistencies arising from this difference, comparable sampling criteria were applied across both datasets, including the selection of recent tweets, exclusion of retweets, and balanced gender representation. However, this methodological variation constitutes a limitation and may affect the comparability of the datasets.

Twitter was preferred to other similar media as it is a public service that is open to everyone and provides a large-scale data with variant people and topics. When compared to other social media services, Twitter is more preferable among adults, academicians, politicians, and celebrities that offer the chance to take a wide range of participants into consideration. The platform is particularly relevant for sociolinguistic inquiry because it combines brevity, public visibility, interactivity, and topic-based circulation through hashtags and mentions, all of which may shape lexical choice and identity performance in distinctive ways.

It is possible to follow tweets by anyone as long as you are a member of Twitter; however, a program was needed to download tweets of others we were not following as a wide range of participants were used in this study. That is, the first data in 2015 was collected by the program named as Wamp Server to download tweets and make the corpus for this study.

- Localhost/Twitter API was programmed; recent tweets were downloaded
- Tweets were chosen randomly (400 was chosen out of 2K tweets; 200 male/ 200 female)
- Test/ training data were held out (80 % test data; % 20 training data)

In 2025, data was recollected through the social media Twitter (X) in the same way. However, as the Wamp Server was not accessible to the authors anymore, 2025 data was collected manually:

- 200 tweets were chosen randomly (recent tweets were copied)
- Test/ training data were held out (80 % test data; % 20 training data) to examine classifier confidence for gender attribution.

We have chosen users' tweets with a gender assignment rather than unmarked users. The gender assignment was checked manually in both 2015 and 2025 data regarding profiles, first names and photos, but Twitter authors personal information, names and accounts were not shared in the study due to the personal rights of the authors. It was assumed that Twitter authors tend to use their true names although there might have been exceptions at an unimportant level. Retweets were also excluded.

Gender classification was based on publicly available profile indicators such as usernames, profile descriptions, and profile images. While this approach is consistent with prior large-scale social media studies, it is subject to potential inaccuracies due to pseudonymity, non-binary identities, and performative self-presentation in digital environments. Accordingly, the gender labels used in this study should be interpreted as inferred rather than verified identities, and the findings should be considered within this limitation. This limitation is particularly relevant in digital environments where identity performance may not align with offline demographic categories.

Classifier confidence

Although the profile, names and photos project the gender of the Twitter authors, Twitter still has user latency beyond the information published. As such, we assigned gender to the Twitter author and measured whether the language carried gender information or not. To do this, training data were used, and gender classification of the authors was compared to the explicit gender fields. The declaration of the Twitter author was accepted as the ground truth for the gender of the author. However, because digital self-presentation may not accurately reflect offline identity, and because users may adopt pseudonyms, ambiguous profile cues, or non-binary identifications, this procedure should be regarded as an inference-based classification rather than a verification of users' actual identities. Any of this information in terms of the authors identities were shared in this paper.

Data analysis

To examine classifier confidence

In 2015, 20 percent of the whole data (80 out of 400 tweets) were examined as the training data. The percentage of accuracy regarding gender attribution was calculated by comparing gender classification of the author and the explicit genders of authors by checking the profiles in Twitter.

In 2025, 20 percent of the whole data (80 out of 400 tweets) were examined as the training data. The same proportion was intended in the 2025 dataset; however, due to the smaller corpus size, the absolute number of cases differed across years. In the same way, the percentage of accuracy regarding gender attribution was calculated by comparing gender classification of the author and the explicit genders of authors by checking the profiles in Twitter (X).

To examine lexical variations based on gender

Downloaded tweets were examined to see whether they show any variances based on gender. As being different from conventional methods that focus on lexical items that are regarded as female or male gendered, this study adapted the reversed 'regularization' method of Bamman et al. (2014) by examining words and word-like items as independent variable and gender turns out to be the dependent variable. As such gender does not decide on lexical variation, whereas the frequency of a word that was repeated by men and women decides the gender identity.

The data were divided into two; test and training data so as to decide on the accuracy of the classifier. 80 % of the data were used as training data while 10 % were used as test data and 10 % were used as to test the gender prediction of the classifier. The fraction of each word was counted as male or female. These percentages were compared with the fraction of the total.

Training data were examined based on some certain categories. These categories were adapted from previous studies (Bamman et al., 2014). The categories are as follows;

Named entities; *people, places, things*

Taboo words; e.g. sex, make love, prostitute

Swear words; e.g. *toff, gob shite*

Numbers

Emotion terms and emoticons; e.g. *love, glad, sorrow*

Kinship terms; e.g. *mother, mommy, aunt, father, auntie, bro, wife…*

Abbreviations

Hashtags; *any word following #*

Pronounceable dictionary words; e.g. *nope, nah, haha, lol*

Non-pronounceable dictionary words; e.g. *omg*

The authors' tweets were examined in *clusters.* Clusters represent the words by the same author, and they were formed without considering gender. Similar tweets that had similar words and were in similar length were grouped by using N-vivo 10. The analysis focused on the distribution of lexical categories across groups rather than on isolated lexical items alone, allowing for a broader comparison of discourse tendencies within each dataset.

To examine homophily on Twitter and Twitter (X)

An undirected social network from direct conversations was constructed. Twenty users' tweets were taken into consideration ten years apart from 2015 to 2025. Twitter authors homophily tendencies were observed based on the data and whether the gender composition of a Twitter author suggests any information about the gender. The statistical hypothesis for this is to see how gender composition of these twenty tweeter authors' individual networks would diverge from 50 percent male / female balance. The cumulative distribution of twenty participants was measured under binominal distribution (p=. 50) and N= (number of friends).

The analysis of gender homophily was conducted on a relatively small sample (n = 20 per group), which may limit the generalizability of the findings. Accordingly, the results related to network structures should be interpreted as exploratory rather than definitive.

Findings

Classifier confidence

The accuracy of Twitter and Twitter (X) authors' gender attributes were analyzed by checking the explicit gender profiles manually.

The accuracy of gender attribution was examined by comparing inferred gender classifications with publicly available profile indicators. In the 2015 dataset, the classifier showed relatively higher alignment rates compared to the 2025 dataset.

The data of 2015 Twitter authors' accuracy percentage of 20 % of whole data was 80 tweets. The data of 2025 Twitter (X) authors' accuracy percentage of 20 % of whole data was 40 tweets in total, were shown in Table 1.

Table 1: The accuracy of gender attributes.

Gender	**Tweets**	**Gender attribute accuracy**	**Percentage**
Female (Twitter author)	43	38	**88.3%**
Male (Twitter author)	37	31	**83.7%**
Female (X author)	24	17	**70.8%**
Male (X author)	16	13	**81.25%**

The results showed that gender attribution of the classifier was accurate more than 50 % for the 20 % of the data for both 2015 Twitter and 2025 Twitter (X) authors. Female and male users' tweets were not equal as they were chosen without checking the explicit genders; however, the percentage for each was calculated separately.

Lexical variations based on gender

Lexical variations in female and male language use on social media were analyzed with the help of N-vivo 10. The data were classified by coding with the help of N-vivo 10 and word frequencies for each gender was calculated and 2015 data presented in Table 2 and 3. During the analysis, two more codes emerged, which are romantic, and politics related words.

2025 data was presented in Table 4 and 5. During the analysis, one more code emerged, which is natura related words.

The frequency results of female and male authors for each category were compared with the help of ANOVA- One Way (SPSS Version 15) to examine whether there was significant difference. ANOVA test was preferred as the number of participants were more than thirty (N > 30) and the groups were independent. While formal assumption testing (e.g., normality and homogeneity of variance) and **effect size calculations** were not explicitly reported, the analysis provides an indicative overview of distributional differences across categories.

The results were presented below.

Table 2: One way ANOVA results for each variable, sorted by lexical variation (2015 Twitter authors).

	NE	**TW**	**SW**	**N**	**#**	**EW**	**E**	**KW**	**ABB**	**NPD**	**PD**	**PW**	**RW**
Female	$\overline{x}_{sıra}$=6; 8	$\overline{x}_{sıra}$=4; 1	$_{sıra}$=5; 2	$\overline{x}_{sıra}$=2; 5	$\overline{x}_{sıra}$=22;82	$\overline{x}_{sıra}$=2; 0	$\overline{x}_{sıra}$=22; 9	$\overline{x}_{sıra}$=9; 3	$\overline{x}_{sıra}$=6; 6	$\overline{x}_{sıra}$=4; 4	$\overline{x}_{sıra}$= 2;3	$\overline{x}_{sıra}$= 4; 4	$\overline{x}_{sıra}$=11; 21
Male	p> .05	p> .05	p>.05	p>.05	**p<.05**	p>.05	**p< .05**	**p< .05**	p> .05	p> .05	p>.05	**p< .05**	**p< .05**

*****NE= Named entities; TW= Taboo words; SW= Swear words; N=Numbers; # = Hashtags; EW= Emotion words; E=Emotions; KW= Kinship words; ABB= Abbreviations; NPD= Non-pronounceable words; PD= Pronounceable words; PW= Political words; RW=Romantic words.

Table indicated that female and male authors differ in their use of language mostly. Female and male authors did not differ in terms of named entities, taboo and swear words significantly, though female authors used slightly more taboo and swear words than male authors (*p<.05;* $\overline{x}$ =4.1; $\overline{x}$ =5.1). Concerning abbreviations, female and male authors did not indicate any difference.

Regarding numbers, female and male authors recruit more words with numbers when compared to female authors (*p<.05;* $\overline{x}$ = 2.5) and male authors had more romantic words, as well.

Emotion words and emoticons were more in female tweets compared to male tweets. Emotion words did not indicate a significant difference while emoticons were significantly more in female tweets (*p<.05;* $\overline{x}$ =2; 0). Similarly, kinship terms appeared significantly more in female tweets (*p<.05;* $\overline{x}$ =9.3).

Regarding pronounceable dictionary and non-pronounceable dictionary words, the results did not indicate a significant difference while male authors used slightly more pronounceable and non-pronounceable dictionary words.

Results also indicated that female authors' tweets were more oriented with political words (*p<.05;* $\overline{x}$ =14.4) and female authors' tweets had more words that refer to romanticism (*p<.05;* $\overline{x}$ =11.21). Political and romantic categories emerged while analyzing the tweets. Political words included the tweets that refer to political issues while romantic words included love words, such as lower, kiss, love.

The frequency results of hashtags also indicated a significant difference between male and female tweets (*p<.05;* $\overline{x}$ =122.82). Female authors had more hashtags compared to male authors.

To examine gender in language use independent of gender stereotypes, tweets were clustered with the help of N-Vivo 10 based on similar words. 7 clusters were formed without considering gender but similar words. The reason why clusters were formed without taking gender into consideration is to examine whether language on Twitter is really gender based and to investigate language free from the stereotype codes. The results were shown in Table 3.

Table 3: Clusters based on lexical variations, sorted by word class (2015 Twitter authors)

Word class%	**Female %**	**Male %**	**Named entities**	**Taboo words**	**Swear words**	**Numbers**	**Emotion words**	**Emoticons**	**Kinship terms**	**Abb.**	**Hashtags #**	**Pd words**	**Npd words**	**Romantic words**	**Politic words**	**Top words**
C1	10	10	3				1				8					#religion
C2	16	7			4	2		1	3		10	1		1	1	
C3	13	8				1		1	3		15			1		# HAPPINESS
C4	12	6						10			12					
C5	8	15				3					10	1			1	# freedom
C6	8	14				3		0	1		14		1		2	
C7	16	9		1				3	2		16				9	#INEQUALITY
Total																

** PD = Pronounceable dictionary words; NPD = Non-pronounceable dictionary words; Abb.= Abbreviations*
** The percentages of word classes and lexical variations*

The results indicated that though clusters were formed free of gender, almost all of them were found gendered except for cluster 1. Cluster 1 (henceforth; C1) was equal in terms of male and female distribution.

C2 had swear, politic and romantic words and it was female skewed. In accordance with gender-oriented analysis, C3 which had many kinship terms was female skewed while C5 which had many number words was male skewed. Similarly, the results of C7 were in accordance with the first analysis that was shown in Table 3. C7 had many political words, and it was female skewed and had many emoticons in it. C6 was a male skewed group, and numbers became prominent in this cluster.

Ten years later, in the same way lexical variations in female and male language use on the new version of 2025 Twitter (X) were analyzed with the help of N-vivo 10. The data were classified by coding with the help of N-vivo 10 and word frequencies for each gender was calculated and presented in Table 4. In comparison to 2015 Twitter, newly emerged category political words hardly appeared, and romantic words category continued its existence by getting stronger. Additionally, nature words emerged as a new category with frequent use of related words.

Table 4: One way ANOVA results for each variable, sorted by lexical variation (2025 X authors).

	NE	**TW**	**SW**	**N**	**#**	**EW**	**E**	**KW**	**ABB**	**NPD**	**PD**	**PW**	**RW**
Female Twitter(X) author	$\overline{x}_{s\imath ra}$=26; 28	$\overline{x}_{s\imath ra}$= 1; 2	$\overline{x}_{s\imath ra}$=1; 1	$\overline{x}_{s\imath ra}$=4; 3	$\overline{x}_{s\imath ra}$=110;170	$\overline{x}_{s\imath ra}$=85; 50	$\overline{x}_{s\imath ra}$=100; 70	$\overline{x}_{s\imath ra}$=15; 10	$\overline{x}_{s\imath ra}$=1; 1	$\overline{x}_{s\imath ra}$=0; 0	$\overline{x}_{s\imath ra}$=1;1	$\overline{x}_{s\imath ra}$= 5; 6	$\overline{x}_{s\imath ra}$=39;20
Male Twitter(X) author	p> .05	p> .05	p>.05	p>.05	**p<.05**	**p<.05**	**p< .05**	**p< .05**	p> .05	p> .05	p>.05	p>.05	**p< .05**

*****NE= Named entities; TW= Taboo words; SW= Swear words; N=Numbers; # = Hashtags; EW= Emotion words; E=Emotions; KW= Kinship words; ABB= Abbreviations; NPD= Non-pronounceable words; PD= Pronounceable words; RW=Romantic words; NW= Nature words

Table 5 indicated that female and male 2025 Twitter (X) authors differ in their use of language in the use hashtags, emotion words, emoticons and romantic words. Female and male 2025 Twitter (X) authors did not differ in terms of named entities, taboo and swear words, numbers significantly, and more significantly, abbreviations, NPD and PD words hardly appeared in 2025 (X) authors' tweets.

Regarding emotions and emoticons, female X authors recruit more words when compared to male authors (*p<.05;* $\bar{x}$ = 65,50) and male authors had more named entities and hashtags, as well. Similarly, kinship terms appeared significantly more in female tweets (*p<.05;* $\bar{x}$ =25, 20). Results also indicated that female 2025 (X) authors' tweets had more words that refer to romanticism (*p.05;* $\bar{x}$ =25, 20).

When compared to 2015 Twitter and 2025 Twitter (X) authors results, there are some differences in terms of predominant use of romantic words and kinship words by female 2025 (X) authors. More importantly, new emerging political words category of 2015 Twitter hardly appear in 2025 Twitter (X) platform though a new category with nature words came out with corresponding amount of use by both genders.

To further synthesize the findings across both datasets, Table 6 presents an interpretive comparison of relative differences across lexical categories based on observed group means. This comparison provides a descriptive overview of variation across categories beyond statistical significance.

Table 5: Interpretive comparison of relative differences across lexical categories (2015–2025 Datasets).

Variable	**Female (m)**	**Male (m)**	**Significance**	**Relative magnitude**	**Interpretation**
Hashtags	110	170	p < .05	High	Male-dominant
Emotion words	85	50	p < .05	High	Female-dominant
Emoticons	100	70	p < .05	High	Female-dominant
Kinship words	15	10	p < .05	Moderate	Female-dominant
Relationship words	39	20	p < .05	High	Female-dominant
Named entities	1	2	n.s.	Minimal	No clear pattern
Taboo words	1	2	n.s.	Minimal	No clear pattern
Swear words	1	1	n.s.	None	No difference
Numbers	4	3	n.s.	Minimal	No clear pattern
Abbreviations	1	1	n.s.	None	No difference
Political words	5	6	n.s.	Minimal	No clear pattern
Nature words	40	43	n.s.	Minimal	No clear pattern

These relative magnitude categories are based on observed differences and should be interpreted as indicative rather than standardized effect size measures. Overall, the findings suggest that gender-based lexical variation is not uniformly distributed across categories but appears to be concentrated in specific domains, particularly those related to emotional expression and social interaction. In contrast, several categories display minimal or no variation, indicating that gendered patterns in digital discourse may be selective rather than pervasive.

To examine gender in language use independent of gender stereotypes, tweets were clustered with the help of N-Vivo 10 based on similar words in the same way for 2025 Twitter (X) authors. 5 clusters were formed without considering gender but similar words.

The results were shown in Table 7.

Table 6: Clusters based on lexical variations, sorted by word class (2025 X authors).

Word Class%																	
	Female %	**Male %**	**Named entities**	**Taboo words**	**Swear words**	**Numbers**	**Emotion words**	**Emoticons**	**Kinship terms**	**Abb.**	**Hashtags #**	**Pd words**	**Npd words**	**Romantic words**	**Politic words**	**Nature words**	**Top words**
C1	17	23	10	1	1	2	17	36	3		76			8	1	14	# HAPPINESS # freedom #INEQUALITY #sun #nature #love
C2	23	19	15	1		3	49	50	6	1	43	1		23	2	23	
C3	20	22	5			1	20	23	4		70			11	2	16	
C4	18	20	12	1		1	16	24	5	1	54			5	3	15	
C5	22	16	12		1		23	37	7		37	1		22	3	6	
Total																	

** PD = Pronounceable dictionary words; NPD = Non-pronounceable dictionary words; Abb.= Abbreviations*
** The percentages of word classes and lexical variations*

The results in clusters indicate that clusters which are female skewed, such as C2 and C5 were found to be predominant with emotion words, emoticons, romantic and kinship words while male skewed clusters, such as C1 was found to be predominant with hashtags. More significantly, when compared to 2015 Twitter authors (see Table 4), 2025 Twitter (X) authors' results scatter more proportionate in terms of named entities, political words, numbers of PD words, NPD words and nature words. As another difference, while political words cluster was predominantly female skewed previously, 2025 results indicate a more even distribution and the emerge and rise of nature category with an increasing number of vocabulary.

Gender homophily

20 female and 20 male Twitter authors were randomly recruited to examine gender homophily. Each authors' Twitter connections were examined based on binomial parameters. In each network, the contacts without gender such as, groups, clubs were excluded.

To update the results for 2025 Twitter (X) authors, 20 female and 20 male Twitter (X) authors were randomly recruited to examine gender homophily. Each authors' Twitter connections were examined based on binomial parameters as well. The results for both were shown in Table 8.

Table 7: The distribution of gender on authors' network and gender homophily(from 2015 to 2025).

2015Twitter Authors	**# Following (total)**	**# female / # male *f***	**Percentage %**	**2025 Twitter (X) Authors**	**# Following (total)**	**# female / # male *f***	**Percentage %**
Female author	115	Female 48 Male 67	Female 41.73 %	Female author	1,934	Female 1224 Male 710	Female 63.28%
Female author	183	Female 90 Male 93	Female 49.18%	Female author	303	Female 170 Male 133	Female 56.10%
Male author	190	Female 22 Male 168	Male 88.42%	Male author	506	Female 401 Male 105	Male 20.75%
Male author	641	Female 403 Male 238	Male 37.12%	Male author	709	Female 403 Male 306	Male 43.15%
Female author	308	Female 76 Male 132	Female 24.67%	Female author	4,492	Female 2,102 Male 2,390	Female 46.79%
Female author	194	Female 82 Male 112	Female 42.26 %	Female author	890	Female 375 Male 515	Female 42.13%
Male author	186	Female 40 Male 146	Male 78.49 %	Male author	703	Female 479 Male 224	Male 46.76%
Male author	116	Female 35 Male 71	Male 61.20%	Male author	1,673	Female 900 Male 773	Male 46.20%
Female author	186	Female 56 Male 120	Female 30.10 %	Female author	2,302	Female 958 Male 1344	Female 41.61%
Female author	559	Female 130 Male 149	Female 23.25%	Female author	402	Female 150 Male 252	Female 37.31%
Male author	175	Female 53 Male 102	Male 58.28 %	Male author	256	Female 104 Male 152	Male 59.37%
Male author	237	Female 154 Male 83	Male 34.29%	Male author	1,360	Female 864 Male 496	Male 36.47%
Female author	242	Female 58 Male 120	Female 23.96 %	Female author	2,200	Female 1004 Male 1196	Female 45.63%
Female author	101	Female 32 Male 69	Female 31.68 %	Female author	608	Female 378 Male 230	Female 62.17%
Male author	168	Female 55 Male 113	Male 67.26%	Male author	1,113	Female 700 Male 413	Male 62.89%
Male author	62	Female 13	Male 79.03 %	Male author	1,406	Female 621	Male 55.83%

		Male 49				Male 785	
Female author	64	Female 29 Male 35	Female 45.31%	Female author	675	Female 400 Male 375	Female 59.25%
Female author	44	Female 16 Male 28	Female 36.36%	Female author	809	Female 455 Male 354	Female 56.24%
Male author	198	Female 68 Male 130	Male 65.65%	Male author	345	Female 128 Male 217	Male 62.89%
Male author	191	Female 31 Male 160	Male 83.76%	Male author	1,205	Female 705 Male 500	Male 41.49%

The previous and recent results of Twitter authors differ from each other considerably in terms of gender homophily. That is, the previous results of Twitter indicated that randomly chosen 10 female Twitter authors had more male contacts than female contacts. In that, female authors' contacts did not show any sign for gender homophily. None of the female authors' fellow contacts exceeded 50 %. On the other hand, 8 out of 10 randomly chosen male authors had more male contacts than female contacts, which was at around 80 %. In that, male authors showed homophily signs of gender in their network connections.

On the contrary, 2025 results of Twitter (X)'s randomly chosen 10 female authors had an even distribution among male and female contacts, with 5 more female; 5 more male fellow contacts. As regards male X authors, unlike previous results they had a tendency of having more female contacts with 6 out of 10 authors' female exceeded fellow contacts. In that, 2025 Twitter(X) authors showed no sign of gender homophily.

Discussion of results

As it is referred in literature review, previous studies in the literature have indicated that female-authored discourse is oriented with emotion (Bamman, 2014), kinship and romantic words while male language is equipped with numbers (Ikae & Savoy, 2022), non-emotional, dictionary, taboo (Bamman, 2014) and swear words. However, this study results were not completely in accordance with previous studies and indicated a different language on Twitter. In addition, the results were presented in comparison ten years apart from 2015 to 2025 indicating variances in terms of predominance lexical variance by female and male social media users and gender homophily.

In addition, while certain patterns appear to diverge from traditional gendered language norms, these findings should be understood as context-dependent and reflective of specific digital environments rather than universal linguistic behaviors.

Building on this pattern, the findings indicate that gender-based lexical variation in digital discourse is not evenly distributed across all categories but is instead concentrated in specific domains, particularly those related to emotional expression, interpersonal communication, and relational language. This suggests that gendered language use in social media contexts operates selectively rather than systematically, challenging earlier assumptions in the literature that portray gender differences as stable and pervasive across linguistic features (e.g., Lakoff, 1975; Tannen, 1993; Bamman et al., 2014). This finding also aligns with more recent perspectives that conceptualize gender as a context-dependent and performative construct, enacted through discourse and interaction (Butler, 1990).

These findings are also consistent with recent empirical research on digital communication, which suggests that gendered language use in social media is neither fixed nor uniformly distributed across contexts. For example, Arshad et al. (2022) demonstrate that while women tend to adopt more relational and supportive linguistic styles, and men more assertive forms of expression, such tendencies are shaped by interactional and contextual dynamics rather than stable gender traits. Similarly, Romadloni and Sari (2025) report that although women's language on X (formerly Twitter) appears more emotionally expressive, these differences are not always statistically robust, indicating variability across datasets. In line with this, Elmahdi et al. (2024) highlight that gendered communication patterns are recontextualized in online environments, where platform affordances and user practices play a significant role.

Classifier confidence

The results showed that gender attribution of the classifier was accurate more than 50 % for the 20 % of the data, which meant that the study was reliable in terms of gender attribution.

Lexical variation based on gender

The results were discussed for both 2015 and 2025 results of Twitter separately, and compared in terms of variances.

2015 Twitter results indicate a discrepancy between female and male Twitter authors at almost each lexical variations though all of them do not show a significant difference.

First of all, taboo and swear words outweighed in female tweets. In that, in contrast to the expected result based on literature, female Twitter authors used more taboo and swear words on Twitter. It can be suggested that this does not mean male users do not use taboo and swear words; however, they are certainly not 'manly' words but 'womanized' to some extend on Twitter or it can be interpreted that these words are genderless on Twitter.

Secondly, female authors' tweets seemed to be politicized as they indicated a significant difference when compared to politic words in male tweets. When politicized mails were investigated, it was seen that they were mostly Iranian or Middle Asian woman authors. However, it should not be forgotten that the study was conducted on a limited data. The reason might be interpreted such that Twitter offered a free platform for female to voice their ideas. They were mostly about freedom and equality. Some examples from female authors tweets as follows;

Twit : In Congress, Income Inequality Fact of #Life for Food Servers - #ABCNews http://t.co/3vlSrGl03s #eyebalz #buzz
Date : 2015-05-04 09:41:20

Twit: Even Barack filters news and media because it is destructive and toxic #productivity #life… http://t.co/6I1k6jMQpz http://t.co/Qzjdvb09Ed
Date: 2015-05-06 14:41:51

Twit: Empowering patients to take charge of their own #wellbeing for years to come http://t.co/tER8Rdo7fY #wellness #quality #life #tips
Date: 2015-05-07 09:30:46

Regarding romantic words, not in accordance with previous studies, male authors' tweets outweighed female tweets significantly. In that, male Twitter authors seemed more romantic in their use of language. It might be possible to explain with the permissiveness of Twitter environment. Male authors may enjoy being free from social pressure though this is another dilemma. It is believed that romantism make people powerless and weak. As most men see themselves as the symbol of power in society, they avoid using romantic words except for flirting. However, it might be personality rather than gender so when they have the chance to reveal themselves, it might have come out. Some examples from romantic e-mails of males are as follows;

Twit: Good Day Sunshine today you better make plans! #Toronto #MyCity #FeelingGood #Music #Life http://t.co/6Twbh1ZsSg
Date: 2015-05-06 14:42:08

Twit: Beautiful day to embrace a beautiful life!! #DC #LA #Love #Life
Date: 2015-05-06 14:44:33

Twit: #life yup pretty much true http://t.co/0x4eUKk0IM
Date: 2015-05-06 14:43:43

Twit : (11) "the beginning of #love is to let those we love be perfectly themselves.." https://t.co/Cdg6DB1zR8 #change #positive #life #quotes
Date: 2015-05-08 11:30:31

However, female authors still have more emotion related words in their tweets and they use significantly more emoticons. The use of emoticon has been a new way of communication today. It expresses emotions or helps to exaggerate emotions in a direct way. That is, it may be said that emoticon use might be representative for expressing emotions. Female Twitter authors might be interested in sharing their emotions more than male authors. Some examples of female authors' tweets with emoticons;

Twit: #GiveThanks for the #smallThings in #Life Everyday things like running water #Wata Be #Happy You didn't have to run & Get it. Date: 2015-05-06 14:46:40

Twit: Exciting!!!!!!! #vote #election2015 #love #life #choice https://t.co/hv8djfhNXF
Date: 2015-05-07 09:26:01

Regarding kinship terms, female authors' results showed accordance with previous studies and outweighed. Female Twitter authors mentioned their family and relatives more in their tweets. It might be because female authors have more intimate relations within family or they do not exclude their family members on Twitter while male authors may have the tendency to have other connections rather their family members on Twitter. Some examples from female tweets were as follows;

Twit: Swing your swing #DamiaKamelia #mother #daughter #moment #capture #love #life #without #beach… https://t.co/uQ3Sdwq9bZ Date: 2015-05-07 09:58:00

Twit: Love them! #maciel #salazar #andrade #cousins #primitos #life https://t.co/DNIiaWEGJm Date: 2015-05-07 11:12:11

Concerning named entities, abbreviations, PDW and NPDW, there was not a significant difference; however, hashtags showed a significant difference in support of female Twitter authors. There might be a reason for that as the results mostly indicated the desire for female authors to make themselves visible and take part in society free from gender-biased stereotypes. It was derived from their politicized and non-romantic use of language. Hashtag is a way of taking part in social media and direct interaction. So, women might have the tendency to use hashtags more to participate in social media directly.

As regards clusters, they were formed based on similar words regardless of gender and the results of cluster analysis have confirmed that stereotypical lexicon based on gender cannot be adapted to the digital environment. The clusters with political, swear, taboo, kinship words and emoticons intensive were female skewed, while clusters oriented with more romantic words and numbers were male skewed. That has importance since cluster analysis was independent of stereotyped lexical categories and prejudges regarding female and male lexicon. The clusters were arranged with similar words, and they indicated a gender skew in parallel with already formed categories. The possible explanation might be that virtual environment has reformed the language; however, it still seems gendered.

However, results repeated ten years later in 2025 indicated a more proportionate distribution in terms of lexical variation. Outstanding political words among female authors seemed to disappear and instead female authors' tweets were predominant with emotion words and, similarly, emoticons. On one hand, the platform female authors could have been depoliticized. On the other hand, social media such as You tube, Tik Tok., etc have been pluralised which might have reduced the importance of Twitter as digital platform to express political opinions.

In the same way, 2025 results of Twitter (X) showed a difference in terms of predominant use of swear and taboo words of female authors. Not only female authors but also male authors seemed to avoid using swear and taboo words less. Though the study was conducted on a limited data, the reason might be interpreted such that lynching culture is very popular with fellows on social media currently, which could possibly make authors be more careful and explain themselves to the full with more attentive words.

Another interesting recent result was with romantic words previously in 2015 weighted by male authors as the results were reversed for 2025 Twitter (X) authors. That is, female X authors outweigh male

X authors in terms of the use of romantic words. Some examples from romantic tweets of males are as follows;

Twit: As a quiet rebel searching for deeper truths of who we are and why we're here, I made this in the spirit of freedom. I went with the flow, integrated mistakes, and loved it despite imperfections. Do you think freedom is a state of mind? #Freedom #mind #consciousness Date: 2025-02-07 15:03:10

Twit: Vanilla swirls in silky streams, golden foam rising gently. Sunshine melts into every sip, warmth lingers on sugared lips. Morning unfolds in quiet moments, a café cup of happiness. #vss365 #coffee **#Happiness** Date: 2025-02-07 16:04:03

Differing results from 2015 to 2025 may indicate that digital platform Twitter has transformed its authors' use of lexical variation by gender to some extend which may be influenced by both the changes in the platform itself such as extending word limit, video uploads, users and social changes in the society. In addition, the purpose of the platform might have been transformed by changing social norms or authors' preferences.

Gender homophily

The results of the study from 2015 to 2025 differed with regard to gender homophily. Firstly, the 2015 study results indicated gender homophily among male authors whereas there were no signs of it among female authors. Almost all of the male participants had homophilic connection. These results were therefore surprising, as the issue of homophily on Twitter was gendered.

Male Twitter authors have tended to connect with other male authors more than with female authors. It may be because they feel more comfortable with the same gender and more powerful in groups. Belonging to a group makes people feel stronger. This group may be of the same gender. As discussed, males have the tendency to be powerful. Additionally, groups have power to validate people. Males may need to feel confirmed and powerful more than females do. As mentioned in the literature review, Johnstone confirmed that women's talk involves social power through community whereas men's talk involves power that comes from the individuals themselves (as cited in Tannen; 1993).

In contrast to the male authors, none of the female authors had gender homophily among their network contacts. This suggests that female Twitter authors do not have a tendency to socialise in groups with people of same gender. One might expect women to support each other more and move in groups as they are often perceived as weak and fragile creatures who are vulnerable to danger and expected to lack self-esteem and rapport for each other. However, contrary to expectations, female Twitter authors are more open to communicating with men than women, and do not show any predisposition to being in groups or communicating with people of the same gender. This may be explained by the new virtual societal norms that offer women a degree of freedom they have never experienced before.

Conversely, unlike 2015, recent results from Twitter (X) 2025 indicated no gender homophily among male and female authors, which might reinforce the notion that the digital social world has its own rules and is subject to change based on its own social norms. This suggests that male authors might be adapting more slowly to this new world than female authors, or that the Twitter digital society is becoming more like a community.

This study examined lexical variations and gender homophily on Twitter, categorized by gender. The results of the research questions can be summarized in four aspects: 1) Language on Twitter is gendered; however, it is almost completely different from the stereotypical gendered language in society. The newly born digital environment may have reformed language how it is interpretated in this new society, which seems to be free from conventional social codes; 2) While some lexical categories such as abbreviations, named entities, NPD words and PD words did not indicate a significant difference between female and male Twitter authors the other categories indicated a significant discrepancy compare to previous studies

(Burger et al., 2011; Bamman et al., 2014; Halteren & Speersta, 2014) and the present study. Hashtags and political words appeared more frequently in female tweets, whereas romantic words appeared more frequently in male tweets. Additionally, swear and taboo words appeared more frequently in female tweets. Kinship terms and emoticons, however, did not differ from previous studies, and were found to be out more prevalent in female tweets. However, these results were reversed for 2025 Twitter (X) authors. Hashtags appeared more frequently in tweets by male authors and were not predominant in political words while romantic words appeared more frequently in tweets by female (X) authors. Also, swear and taboo words showed no significant difference appeared rarely. 3) Clusters were formed based on similar words, regardless of gender, and it was found that the clusters produced similar results to those of the previous analysis. Clusters containing more political, swear and taboo words were female-skewed, while clusters containing more romantic words were male-skewed. The opposite was true for 2025 Twitter (X) clusters. Clusters with a high number of romantic and emotional words, and emoticons were female-skewed, while hashtag-intensive clusters were male-skewed. Swear and taboo words were distributed fairly evenly. 4) In contrast to previous studies (Bisgin et al., 2010; Zamal et al., 2012), male authors' network connections showed strong indications of gender homophily while female authors' network connections were almost balanced and even slightly male-skewed. The 2025 Twitter (X) platform did not confirm this either, indicating no gender homophily for either female or male authors.

Regarding the above strands, several interpretations can be offered as to why the so-called 'manly' lexicon has been exchanged for the 'female' lexicon. One possible explanation is that the environment has changed from real society to a virtual one. This could have led to variety in vocabulary and language use. Secondly, users of language may have changed in parallel with changes in the world. Particularly, female authors in 2015 seemed to show a tendency to declare their freedom from social codes that restrict and shape their speech in both their choice of words and their use of language. Furthermore, it has been suggested that women may praise individualism more in the new digital society, as it has been observed that women do not primarily socialize with people of the same gender. However, within ten years, the digital society more closely, where women's softer communication is more widely accepted and men communicate more freely. In addition, political words appeared to replace natural words, which may indicate a change in societal preferences and interests. Compared to 2015 results, there was a decrease in swear and taboo words in 2025, particularly among female users. This may indicate an increase in the way society expresses itself on digital platforms, or it may be that female users have already established their own views and their anger subsided.

In summary, the results of this study have indicated that social media and the virtual society are changing the language in terms of gender. This was found to be true even within constraints of Twitter' 140-character limit in 2015 and its developed form in 2025. The communication style has become more open to everyone with access to social media; it is not the gender that decided the choice of word, but rather the environment and the topic. Currently, the virtual environment on Twitter indicates that female and male authors seem exchange roles in terms of lexical choice. However, ten years from now, it may resemble real society more closely, and it can be presumed that, in the future, the language of virtual society can be completely gender-neutral and transparent.

Based on statistical results, it can be concluded that male and female-authored discourse use differs, and both Twitter and Twitter (X) platforms have a gendered language. However, while the gendered language on Twitter in 2015 mostly differed from the stereotypical female and male language used in real society, Twitter (X) in 2025 seemed more like the language used in real society.

The reason why the language used in Twitter differs from the language used in society is perhaps because people feel freer from the social codes and social pressures of society that influence speech and language. In society, it is a well-known fact that female and male children are socialized into using gender-typical language, though this starts at slightly different ages, from the time when they start uttering their first words. Boys are encouraged to use harsh words and are mostly stopped from being emotional or using romantic language. They are also made to watch cartoons whose plots are mostly involve war or fight. Even their games involve swords, guns, fight and cars which symbolise bravery, strength, courage, mastery and speed. As such, it is an inevitable that males may end up with a language distilled from emotion and shaped accordingly. Similarly, female children are modelled by others and encouraged to use language that is free from swear and taboo words. Once they utter a word which is not 'suitable' to the society, they are warned harshly and reminded that it is not appropriate for a woman to use utter a ''manly' word.

Another reason might be that gendered language is not completely a biological code, as the society suggests, but mostly a social one. When the environment changes, language evolves in accordance with the new environment, as well as reflecting what people bring from their own backgrounds. Twitter is a new environment offering freedom and the chance to use the language without fear of judgement from the immediate environment. Twitter is like a community; however, users communicate through a screen that makes them feel safe from direct criticism. On the other hand, Twitter is a community in which criticism is accepted. Some people may even carry the identities and the language they use in real society to this new virtual environment. In particular, female users may luxuriate in this virtual environment to relish their free use of language as they wish.

Another factor that should not be overlooked is that Twitter 2015 was limited to 140 characters. This may be another reason why Twitter authors needed to be direct, clear, and concise in their explanations. This is why every author, regardless of gender, used direct language on Twitter. However, authors in 2025 are freer to express themselves without limitations, which is why their tweets are longer and more expressive.

Additionally, Twitter has a feature that provides an opportunity for interactive media, so Twitter authors also use language to participate in TV programs. It is clear that Twitter language also differs according to the context. It is freer among friends, but changes in other contexts. Intimate chatting is not always possible in society but it is on Twitter. This study examined samples of intimate conversations between friends to reveal the elements of vernacular language.

On the other hand, over time, people have become familiar with digital platforms and as they have adjusted to this new world, it has become more like the real society. The number of people using digital platforms increased dramatically transforming existing online communities into a real community. This could explain why the 2025 Twitter (X) results were not in line with the 2015 results.

Implications

The results of 2015 and 2025 data to explore and compare the lexical variations on Twitter and Twitter (X) as social networks based on gender and gender homophily indicated variances ten years apart. In 2015, the language of digital environment differed from the non-virtual environment. The virtual/digital environment offered a completely different social context to its users. This context was free from suppressions, expectations, limitations, codes, roles and forms that are imposed by the society. The findings suggest that this newly formed society showed variances in terms of lexicon from the language in non-virtual environment regarding gender. Though biological differences make a slight change in language use such as tone of voice, it is the society that determines linguistic evolution (Vygotsky, 1987) more that inborn differences. In that, 2015 Twitter re-formed the language in its own context as being different from conventionally gendered language in society.

However, 2025 Twitter (X) results indicated a more even distribution and a language more similar to real society in terms of gender-coded language use (Bamman et al., 2014; Halteren & Speersta, 2014). While 2015 results indicate a gender-reversed language use in digital platforms, 2025 results seemed to be closer to the gender language of the society.

As such, it would be wise to take this into consideration, since it may show that today's world which is oriented with technology is forming the language again and genders may be exchanging the roles in the use of language or in time language may be getting genderless in virtual contexts and may be ten years apart from today it will be "gender-blind" (Pedersen and Macfee, 2007).

This finding has implications for lesson designs. That is, pedagogy might give preference to changing society and language through social media over those that students are restricted around predetermined codes. New lesson designs may include social media and get introduced with changing language use in newly born digital societies.

Many other studies of this area are needed; the factors such as nationalities, status and family backgrounds could be added to the participants and more detailed, longitudinal further studies in the field could be conducted. Also, rather than gender, many other variances and interactions on social media networks are needed to be studied to show whether the language is reforming in virtual society in all aspects.

Limitations

The study was conducted with a limited number of tweets and the number of Twitter authors with various backgrounds can be added in forthcoming studies. Language is not limited to English though English is used as a lingua franca by some non-natives. In that, the study might be conducted in different languages as well as Turkish in Turkish Twitter context in forthcoming studies and the results might be compared with the use other languages on Twitter regarding gender.

Secondly, the datasets from 2015 and 2025 differ in size and data collection procedures, which may affect direct comparability. Gender classification also relies on inferred profile information, which may not accurately represent users' identities, particularly in the context of non-binary or anonymous accounts.

Third, the statistical analysis does not include effect size calculations or formal testing of ANOVA assumptions, which limits the interpretative strength of the findings. Additionally, the analysis does not control for potential confounding variables such as cultural background, topic variation, or platform-specific affordances, which may influence language use.

In addition, Twitter (X) platform tweets were compiled and examined manually which limited the number to 200 tweets, which restricts the generalizability of network-related conclusions. Future research should employ larger datasets and more advanced statistical modeling to address these limitations.

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Appendix

Appendix A.

Table 8: The lexical variations based on gender.

Gender		Named entities	Taboo words	Swear words	Numbers	Emotion words	Emoticons	Kinship terms	Abbreviations	Hashtags	Pd words	Npd words	Politic words	Romantic words
2015	Female	6	4	5	2	2	22	9	6	122	2	4	14	11
	Male	8	1	2	5	0	9	3	6	82	3	4	4	21
2025	Female	26	1	1	4	85	100	15	1	110	1	0	5	39
	Male	28	2	1	3	50	70	10	1	170	1	0	6	20

** PD = Pronounceable dictionary words; NPD = Non-pronounceable dictionary words*

** Word frequency in female and male tweets*