Michael Senko and Rob Voigt

# Chapter 19
# Transgressing the binary: A computational approach to gendered reference

## 1 Introduction

The recognition of transgender identities that challenge the traditional gender binary and nonbinary identities that have moved beyond it has spurred ongoing change in English. A novel usage of singular *they* to refer to nonbinary individuals – termed here as nonbinary *they* – has received widespread adoption as well as attention within linguistic research (Ackerman 2019; Conrod 2019b). At the same time, pronominal misgendering (Conrod 2020) and deadnaming (Turton, 2021) have become enmeshed in the larger culture war over "gender ideology" (Borba, 2022).

Within a dialogic framework of gender, misgendering and deadnaming can dehumanize transgender people by rejecting their agency to determine their own identity (Haslam 2006). Here, misgendering occurs during reference, when the use of a third person pronoun does not align with the self-asserted pronoun suite[1] listed by the referent. Deadnaming occurs through use of a transgender individual's former name rather than their asserted, gender-affirming name. Public health research has demonstrated that these practices can negatively impact the mental health and self-conceptualization of transgender people (Johnson, Auerswald, LeBlanc, and Bockting 2019; McLemore 2015). Meanwhile, the gender-affirming usage of names and pronouns, including novel nonbinary *they*, ratifies individuals' gender identity and affords them semiotic agency (Calder this volume). It is thus

**1** Pronoun "suites" comprise the subject, possessive, and object form of a given pronominal, such as *they/them/theirs*. We use the term *listing* to describe how individuals assert these suites as part of their gender identity.

**Acknowledgements:** The first author of this paper is a cisgender, queer man who lists *he*/*him* pronouns. He offers sincere thanks to those friends, peers, mentors, and reviewers, but especially those from transgender and nonbinary communities, who offered critical feedback at many stages of this project's journey from class paper to thesis and beyond. We also emphasize specific appreciation for Ziyun Chew, Annette D'Onofrio, the audience at LavLang28, and the members of Sociogrop and LingMechLab at Northwestern. Any mistakes or oversimplifications are our own.

https://doi.org/10.1515/9783111351568-019

important to understand the distribution, or large-scale usage, of proper names and third-person pronouns used in reference to transgender people.

Despite a surge in popular and academic interest in this topic, there exists little naturalistic data documenting changes in the uptake of gender-affirming language and the social attitudes that predict misgendering and deadnaming. And despite the ubiquity of pronouns and proper names in everyday language, their status as referring elements leaves few opportunities for significant variation to emerge. Besides gendered pronouns, English does not have a functional class that can vary over the lifetime of a referent in accordance with social factors, such as age or status. Conrod (2022) accordingly argues that the English pronominal system in fact behaves more like a system of honorifics than one of grammatical gender. Although the functional classes of English are considered relatively rigid, or resistant to change, the naturalistic variation in uptake precipitated by transgender coming-out events provides an important site at which modification, and indeed innovation, can occur more rapidly than in similar changes within other linguistic domains.

Coming-out events (COE) mark the moment in which transgender individuals publicly align their internal experience of gender with their social performance of it (Zimman 2009). COEs are often accompanied by more-or-less public speech acts that state a novel pronoun suite and/or proper name as part of the process of asserting the individual's gender identity. Misgendering and deadnaming are particularly at issue during COEs, as transgender individuals in part assess the presentation of their transgender identity through the behavioral and linguistic responses of interlocutors (Zimman 2017). In the past few years, high-profile transgender celebrities have utilized Twitter to facilitate their COE. Twitter, as a microblogging platform, has become increasingly common in computational sociolinguistic research due to the availability of large text corpora (Nguyen, Doğruöz, Rosé and de Jong 2016). Indeed, as our research shows, Twitter users generated tens of thousands of tweets in the moments following transgender celebrities' COEs, many of which contain names and pronouns that refer to the celebrity under discussion.

To quantify the uptake of novel names and pronoun suites, we utilize computational linguistic methods to analyze tweets surrounding transgender celebrities' coming-out events. In a corpus analysis of 7 million tweets, we demonstrate the extent to which Twitter users linguistically ratify or reject the diverse gender identities of seven popular celebrities. The "target" data set includes four celebrities, two of whom are nonbinary and list *they* pronouns, one who is nonbinary transmasculine and lists *he*/*they* pronouns, and one transgender woman who lists *she* pronouns. To better contextualize the dynamic change-over-time we expect to see across the target celebrity COEs, we also collect data for a "comparison" celebrity group. The comparison celebrities do not have publicly-documented coming-out events – whether in terms of gender, sexuality, or otherwise – and therefore provide comparative data in which we do not expect to find as much change in pronominal reference over time. The comparison set comprises three celebrities, two cisgender and one transgender, who list either *he* or *she* pronouns.

We find that, in the time period immediately following the target celebrities' COEs, usage of *they* to refer to the two nonbinary celebrities trails behind the usage of *he* and *she* to refer to the two transgender celebrities. However, all four target celebrities are misgendered more than the three comparison celebrities without public COEs. We also find that two celebrities who asserted new proper names as part of their COEs are deadnamed in 17.5% of tweets on average in the months following these events. These findings reveal significant disparities in gender-affirming name and pronoun reference that fall along fine lines of gender, listed pronoun suite, and the historical time period in which the target celebrities came out.

We further show that misgendering and deadnaming tweets significantly co-occur with lexical items representative of binary gender, biological essentialism, and hate speech. Considering that third-person pronouns and proper names are among the first acts of linguistic self-determination that transgender individuals make (Konnelly and Cowper 2020), our results suggest that misgendering and deadnaming often accompany explicitly dehumanizing language. Meanwhile, gender-affirming tweets are significantly more likely to contain lexical items related to transgender identity, the COEs themselves, and celebration.

Surprisingly, our results ultimately indicate that there is no statistically significant effect of time on the uptake of novel gender-affirming names or pronouns. Following a COE, the rate at which Twitter users linguistically ratify the celebrities' gender stabilizes immediately and remains stable for months thereafter. While the computational methods used in this work allow us to unveil such patterns at a large scale, they cannot hope to capture the full nuance contained in each instance of (pro)nominal reference, a complex interactional event that is interpreted in real time by language users. We instead aim to provide a high-level view of this important linguistic behavior, particularly as a speech act that reflects and reproduces gender. By analyzing transgender celebrity COEs specifically, our study offers a snapshot of ongoing change in English while exploring the social attitudes that mediate Twitter users' linguistic responses to these events.

**Content Warning**: this chapter contains transphobic, homophobic, and misogynistic material in Table 19.3 and Table 19.7.

# 2 Background

Gender emerges in part through interaction. Individuals may determine how successfully they express their gender through the behavior of interlocutors; in this sense, gender identity is a “dialogic construction” (Bucholtz and Hall 2004; Zimman 2017). For people who assert pronoun suites or proper names as part of their coming-out events, the linguistic responses they receive thereafter can inform their self-conception and impact their mental health (Johnson et al. 2019). These interpersonal experiences are of course embedded in larger societal trends, such as ongoing linguistic change in the scope of *they* and increasingly volatile culture wars over gender. These developments have been promulgated by several prominent transgender celebrities who came out starting in the 2010s. Their coming-out events are crucial turning points that can shed light onto how linguistic change in progress as well as sociocultural developments interface with large-scale, naturalistic language use. We focus here on the linguistic mechanisms used to assert gender, specific social attitudes that mediate the reception of gender, and the language practices that, in turn, can ratify or reject gender identity.

English now only marks gender information on third-person pronouns, names, and a handful of lexical items, such as *cowboy* or *congresswoman*. McConnell-Ginet (2015) thus argues that English possesses a notional gender system, corresponding to the cultural notions that a language user relies upon when conceiving of and assigning a gender to their referent. This approach captures the sociolinguistic dimension of gender that is produced through interaction and malleable over the lifetime.

In English, the most common third-person pronoun suites are *she/her/hers*, *he/him/his*, and *they/them/theirs*, though these are not the only ones.[2] For transgender people, who do not identify with the sex/gender category assigned to them at birth, the listing of third-person pronouns can facilitate their coming-out event. Through use of the term *listing* pronouns, we capture the folk meaning of the phrase “Michael uses *he/him* pronouns,” which an individual offers for uptake by interlocutors that rely on this information during reference. While pronoun suites do not necessarily and/or directly map onto gender identity, the listing of pronouns as a practice of self identification has rapidly spread throughout the English-speaking mainstream over the last decade. Jones (2021) observed that the pronouns *she*, *her*, *he*, and *him* exhibited the greatest increase out of all tokens in a longitudinal analysis of Twitter users’ biographies from 2015 to 2020. This trend demonstrates

2 Some individuals list neopronouns, such as *ze/hir/hirs*.

how language practices surrounding pronouns and proper names that have been circulating in transgender communities for decades are now receiving adoption in wider circles as matters of linguistic and social justice (Zimman 2017). As a result, attitudes towards gender-inclusive language change have become inextricably linked with attitudes towards the transgender and nonbinary communities in which these innovations originated (Konnelly & Cowper 2020). Yet at the same time, these innovations have become targets of the "antigender" movement (see Baran, Sauntson this volume).

Contemporary research into nonbinary *they* has stimulated a reconsideration of the ways gender information factors into sentence processing and generated novel analyses of the English pronominal system. Not all nonbinary individuals list *they*, nor can *they* only be listed by nonbinary individuals; rather, we utilize the term nonbinary *they* because this specific usage emerged from nonbinary communities (Conrod 2019b), is the most common suite listed by nonbinary people (Darwin 2017; Hekanaho 2020), and is listed by all the nonbinary celebrities in our data. Singular *they* has been found to be more acceptable with a specific, definite antecedent than with a proper name antecedent overall (Bradley, Salkind, Moore, & Teitsort 2019). There is an additional effect of age, where younger language users are more likely to accept the innovation than older language users (Camilliere, Izes, Leventhal, & Grodner, 2021; Conrod 2019b; Hekanaho 2020). Ackerman (2019) argues that the type and token frequency with which an antecedent is referred to by a gendered pronoun or name enters processing as part of an exemplar tier, consisting of observations drawn from personal exposure to (linguistic manifestations of) gender diversity. Transgender individuals and those with greater awareness of transgender people are more likely to accept nonbinary *they* (Ackerman 2018; Camilliere et al. 2021; Conrod 2019b; Hekanaho 2020). Collectively, this research indicates that transgender identity, as well as attitudes towards and experience with those who hold such identities, is a socially meaningful predictor of syntactic change in the scope of singular *they*.

Prior to the present study, there was little research connecting the perception of gender-inclusive language change to the actual deployment of such changes in natural linguistic contexts. The work that does exist suggests that the social factors mediating perceptions of nonbinary *they* might also contribute to misgendering and deadnaming. In a production study, negative implicit attitudes among language users were shown to predict higher rates of misgendering a transgender film character (Conrod 2018). Additionally, only the transgender characters in the film were misgendered. Conrod (2019a) demonstrates that Twitter users more readily used Chelsea Manning's gender-affirming name than her gender-affirming pronoun suite. As with all the celebrities in our data set, the Twitter discussion surrounding Manning is extremely context-dependent; in her case, the observed patterns are intimately tied to discourses of nationalism and the US military. Nevertheless, Manning was misgendered at a higher rate than she was deadnamed.

Beyond the present study, quantitative research on deadnaming is practically nonexistent. Generally, the use of a name in a referring expression reflects the language user's assumption – or conviction, as deadnaming critically illustrates – that the referent is indeed categorized or characterized by that nominal form (McConnell-Ginet 2003). As such, the use of a non-gender affirming name, one that is often assigned to transgender people at birth, can reintroduce feelings of dissonance and gender invalidation. Turton (2021) explores Urban Dictionary entries of Caitlyn Jenner following her coming-out event, finding that deadnaming commentators focus on Caitlyn's potential surgeries and use biological sex terms to characterize her transgender identity. Together, it appears that pronominal misgendering may go unnoticed more often and may be more related to unconscious attitudes than for deadnaming, which tends to be more explicit in its rejection of transgender identity. Of course, cisgender people can also be misgendered, but these practices become demonstrably harmful when they are directed towards people who might harbor dissonance between a former pronoun suite/name and their experience of gender.

Indeed, studies have shown that misgendering can negatively affect the mental health of binary and nonbinary transgender people, particularly through the degradation of their self conception and the accumulation of social stigma (Johnson et al. 2019; McLemore 2015). Meanwhile, Valentine and Shipherd (2018) find that healthcare providers' use of gender-affirming language can mitigate some of the negative mental health symptoms experienced by transgender individuals. Similarly, usage of transgender youth's gender-affirming names across multiple contexts is associated with lower depression and suicidal ideation (Russell, Pollitt, Li, and Grossman 2018). Thus, it is important to uncover the social factors that not only mediate systematic linguistic change but also predict misgendering and deadnaming in online contexts.

Due to the relative nuance with which linguistic researchers must conduct studies on gender and sexual minorities, work in this area tends to be more limited in scale. Yet computational methods offer scholars of gender, sexuality, and language the opportunity to test well-honed theories of identity construction on a larger stage, and explore the mechanisms underlying the dehumanization of marginalized groups. To analyze the language used to dehumanize LGBTQ+ people, Mendelsohn, Tsvetkov, and Jurafsky (2020) conducted a computational analysis of *New York Times* articles from a 30-year time span. Although the authors found increasingly humanizing descriptions of LGBTQ+ people over time, they also demonstrated starkly different patterns for the terms *gay* and *homosexual*, illustrating how computational methods can help tease apart interrelated social meanings. The present study joins this line of work in computational sociolinguistics exploring social bias (Nguyen et al. 2016), turning specifically to the mechanisms underlying Twitter users' (dead)naming and pronominal (mis)gendering of transgender celebrities.

# 3 Methods

The usage of (pro)nominals in tweets surrounding transgender celebrities' coming-out events (COEs) can be understood both distributionally and lexically. In the distributional analysis, we document the prevalence of misgendering and deadnaming in the period before and after the COEs as well as the time-course uptake of gender-affirming language. More specifically, we measure how transgender celebrities' pronouns and names are affirmed relative to those of cisgender and transgender celebrities without publicly documented COEs. In the lexical analysis, we explore the lexical content of tweets that misgender/deadname or gender-affirm a given celebrity to probe whether any correlations exist between these tweets and lexical items indicative of attitudes from both sides of the ongoing struggle over gender. We also examine potential differences between tweets discussing transgender celebrities who list the pronouns *she* and *he* and those discussing nonbinary transgender celebrities who list nonbinary *they*.

## 3.1 Data collection and filtering

Zimman (2020) describes the 2010s as the decade of transgender publicity, during which the visibility of transgender people greatly expanded in popular culture. The latter half of the decade, in particular, saw many prominent transgender celebrities assert their gender identity in publicly-documented coming-out events. Grounding our analysis in the self-determined gender of these celebrities, we explore not how they construct their own identities, but instead how their assertions of gender are linguistically ratified by a population of Twitter users.

Table 19.1 displays information describing all seven celebrities in the data set. Our intention to curate a balanced data set across gender identity and listed pronoun suite was hindered by the high degree of popularity required to facilitate meaningful computational analysis using Twitter data. For example, while a transgender man who lists *he* pronouns without a publicly-documented COE would have rounded out the comparison group perfectly, we were unable to identify such a person with *significant enough* celebrity; that is, they did not generate enough tweets in any given time period to analyze at scale the pronouns used to refer to them in tweets. As such, the seven celebrities in our data set allow us, albeit incompletely, to consider the effects of coming-out event (publicly-documented / not), pronoun suite (*he* or *she* / nonbinary *they*), and gender identity (masc or fem / nonbinary) on affirming (pro)nominal usage among Twitter users.

The target group consists of four transgender celebrities with publicly-documented COEs and sufficient popularity to facilitate meaningful large-scale analysis. We use the terms *trans-binary* and *trans-nonbinary* to refer to two distinct groups in analysis. We do not intend these terms to reflect an imposition of the gender binary onto these celebrities' identities, but rather to identify commonalities in pronoun listing that facilitate computational analysis across celebrities. A pronoun suite is not equal to gender identity – we establish these categories for analytical purposes, but do not contend that only people of certain identities can use certain pronouns, and vice versa. Elliot Page and Caitlyn Jenner are transgender celebrities who both list the traditionally-binary pronouns *he* or *she*, respectively, so we refer to them as the transgender identity and traditionally-binary pronoun suite, or *trans-binary* celebrities. It is important to note that Elliot Page has at times identified as both nonbinary transmasculine and as a transgender man, listing both *he* and *they* pronouns, although Page has stated he prefers the use of *he* over *they* (GLAAD 2021). The other two celebrities in the target group identify as transgender nonbinary and, at the time of analysis, listed only nonbinary *they*. We thus refer to Sam Smith and Demi Lovato[3] as the transgender nonbinary identity and nonbinary *they* pronoun suite, or *trans-nonbinary* celebrities. All tweets were scraped from the 6 months preceding and following the target celebrities' COEs, with Caitlyn Jenner's period extending slightly due to the nature of her COE.[4]

Meanwhile, the **comparison** group consists of one cisgender woman (Doja Cat), one cisgender man (Tom Holland), and one transgender woman (Laverne Cox)

**3** In the time since data collection, Lovato has begun to again list *she/her* as well as *they/them*.

**4** Because Jenner's COE spanned two significant media events, we scraped tweets from the 6 months before her *20/20* Diane Sawyer interview (4/24/2015) and up to 9 months after her *Vanity Fair* cover (6/1/2015). We center the PRONOUN and NAME analysis on the latter date, as it marks when Jenner first asserted her new name and pronoun suite. The total analysis period for Jenner is slightly longer (15 months) than the other target celebrities (12 months).

**Table 19.1:** Demographic and corpus information for the seven celebrities. NOM counts tweets passing a filter requiring the presence of the celebrity's name or handle; this subset is used for analyses on deadnaming. ALTHAND counts tweets passing a series of filters.

| Celebrity | Pronouns | Identity | Twitter Handle | COE Date | Total Tweets | NOM | ALTHAND |
|---|---|---|---|---|---|---|---|
| Target | | | | | | | |
| Caitlyn Jenner | she/her | Trans woman | @Caitlyn_Jenner | 06/01/2015 | 2,613,733 | 2,250,303 | 293,513 |
| Elliot Page | he/they | Transmasculine | @TheElliotPage | 12/01/2020 | 267,027 | 253,842 | 22,930 |
| Demi Lovato | they/them | Nonbinary | @ddlovato | 05/19/2021 | 1,188,029 | | 50,513 |
| Sam Smith | they/them | Nonbinary | @samsmith | 09/13/2019 | 601,835 | | 26,619 |
| Comparison | | | | | | | |
| Doja Cat | she/her | Cis woman | @DojaCat | NA | 1,585,396 | | 84,201 |
| Tom Holland | he/him | Cis man | @TomHolland1996 | NA | 557,482 | | 32,472 |
| Laverne Cox | she/her | Trans woman | @Lavernecox | NA | 252,725 | | 17,221 |

with Twitter accounts but no publicly-documented coming-out events. For Holland and Doja, tweets were scraped in the same 6-month time period after they fully entered the mainstream, from (7/1/2021) to (1/1/2022). For Cox, tweets were scraped in a 2-year period following her *Time* magazine cover, from (8/1/2013) to (8/1/2015).[5] We collected this subset for two main reasons. First, we wanted to compare the target group to a transgender celebrity that did not have a publicly-documented COE. This allows us to explore the relative impact of a celebrity's coming-out event on affirming name and pronoun usage versus the mere fact of transgender identity. Second, we wanted to include cisgender celebrities as a baseline for the distributional analysis and as a procedural check for the lexical analysis. Because previous research suggests that transgender people are misgendered at much higher rates than cisgender people (Conrod 2018), we used tweets referencing cisgender celebrities to ensure the efficacy of the filtering process. And considering the imperfect state of coreference resolution – the process of identifying all expressions in a text that refer to the same entity – it was imperative that we assess how any lexical or user-level effects might be modulated by noise in the filtering process and whether this process was biased in any way (Morton 2000).

All tweets were scraped using the Twitter API v2 in Python using the following query: New Name, #NewName, or @TwitterHandle. For the trans-binary celebrities, who also asserted a new name as part of their COE, we used additional terms: Dead Name, #DeadName, or @DeadHandle.[6] Besides retweets, all types of tweets (main, replies, quotes, etc.) were included in the scrape query. We modified code provided by Twitter[7] to scrape tweets discussing each celebrity over multiple collection periods between December 2021 and March 2022.

After collection, tweets were processed through six increasingly selective filters devised as a more purpose-oriented approach to coreference resolution (Table 19.2). In doing so, we balance a trade-off between precision (likelihood the data consists of tweets where pronouns actually refer to the celebrity) and recall (likelihood the data consists of all tweets that occurred where pronouns refer to the celebrity). This process was selective but generally successful: each successive stage raised the average affirming pronoun rate for cisgender comparison celebrities, for whom we would not expect significant misgendering.

5 A Google Trends search reveled Cox's *Time* cover to be the most prolific moment of her career thus far.

6 Caitlyn Jenner did not have a Twitter account before her COE.

7 https://github.com/twitterdev/Twitter-API-v2-sample-code

**Table 19.2:** The filtering process.

| Filter | Name | Methodology |
|---|---|---|
| 1 | DUP | Removed intra-author duplicate tweets from the data set. We did not remove inter-author duplicates in the likelihood that there would be meaningful, albeit identical, tweets from multiple authors. |
| 2 | NOM | Removed tweets that did not contain either the name/deadname or Twitter handle/dead-handle of the celebrity |
| 3 | PRON | Removed tweets that did not contain any pronouns. |
| 4 | COREF | Made use of a coreference resolution module, neuralcoref, in a discriminative fashion (Clark & Manning, 2016). We removed tweets that contained coreferential relationships between pronouns and any item that was not a celebrity name or handle token. This filter only removed tweets containing third-person pronouns which the model confidently believed referred to other entities. |
| 5 | ALTENT | Used spaCy's named entity recognizer to remove tweets that included recognizable named entities. This filter also removed celebrities that appeared one or more times in a random sampling of 150 tweets from each corpus. |
| 6 | ALTHAND | Removed tweets containing a Twitter handle that did not match the celebrity's handle or deadhandle. |

## 3.2 Processing

Each tweet was tokenized and analyzed according to the celebrity's name and listed pronoun suite. Beyond the raw text of the tweet, metadata was also retained for analysis, including: the tweet id, creation date and time, author id, author username, author name, author biography, author location, number of followers, and number of users following. If the author biography contained a pronoun suite or LGBT+/pride flags, we recorded the presence and type of these tokens.

We calculated total counts of *he*, *she*, and *they* as well as proper name usages. We used pattern matching techniques, or regular expressions, to standardize the individual celebrity data sets and maximize comparability. Pronouns that affirmed or misgendered a specific celebrity, for example, were replaced with standard PRON_AFFIRM or PRON_MISGENDER labels. We thus performed standardizations for (dead)names, Twitter handles, and third-person pronouns. Once standardized, tweet-level counts of names and pronouns were aggregated and averaged by week.

We calculated the affirming pronoun rate by dividing the count of affirming pronouns (those listed by the celebrity after their COE) over the count of both affirming and directly misgendering pronouns (those listed by the celebrity before their COE). This measure thus excludes pronoun suites that were never part of a given celebrity's gender presentation, before or after their COE (tweets containing *she* that discussed Sam Smith, for example). While this approach will certainly exclude instances of harmful misgendering – by-hand analysis confirmed rare but nonetheless nonzero instances of harmful *they*-misgendering tweets discussing Caitlyn Jenner, for example – it it necessary to reduce noisy data, particularly those instances of plural, generic, or indefinite antecedent *they* usages that slipped through the filtering process. For Elliot Page, who lists *he/they*, we calculate affirming pronoun rate with reference only to *he* as affirming and *she* as misgendering, in order to allow for more direct comparability with the other celebrities and because he stated in an interview that he prefers *he* over *they* (GLAAD, 2021). In preliminary data analysis, this metric elicited affirming pronoun rates for the cisgender celebrities that align more closely with our intuitions: pronominal misgendering, whether habitual or intentional, is a rarity for cisgender people (Conrod 2018). Although the number of plural, generic, and indefinite antecedent *they* instances that did not actually refer to the celebrity far outnumbered instances of coreferentially-accurate *they*-misgendering in preliminary analysis, it is regrettable that we were unable to meaningfully consider all instances of misgendering – *they*-misgendering in particular. Additionally, this approach does not align perfectly for Page, as the exclusion of all tweets containing *they* certainly disposed of some tweets where *they* was used to affirm his gender identity.[8] Our coding choices were necessary to meaningfully analyze Twitter data at this scale but necessarily limit the scope and interpretative potency of our results.

We used Automated Dickey-Fuller (ADF) tests (Dickey & Fuller 1979) to calculate whether COEs, as a demarcator of time, statistically impacted affirming pronoun usage. Across the entire analysis period, our assumption is no significant effect of time for the comparison celebrities but a significant effect of time for the target celebrities.

We also wanted to test whether the presence of words in specific lexical categories predicted misgendering/deadnaming and gender-affirming text at the tweet level. We first adapted measures of lexical polarization from Monroe, Colaresi, and Quinn (2008) to explore associations between particular words in the dataset and misgendering/deadnaming as compared to gender-affirming tweets. Looking at tweets directed towards Jenner and Page (the trans-binary celebrities), for example, significantly DEADNAME-correlated items included binary gender terms, biological essentialism terms (*science*, *surgery*, etc.), *gender*, and *sex*, among others.

**8** Average *they* usage increased for Page from 20.17% before his COE to 27.71% afterwards. This ~7% increase is likely reflective of gender-affirming *they* uptake rather than epicene usages.

Meanwhile, NAME AFFIRM-correlated items include COE terms and transgender identity terms, among others.

We unified the inflected forms of these items (lemmatized via SpaCy) and grouped them into eight lexical categories (Table 19.3). We operationalized these lexicons as binary variables at the tweet level: for a given category, did the tweet contain any words present in the category? We used spaCy to split each tweet string into lemmas before cycling each lemma through the eight categories. Each tweet string-lexical category match was recorded (see Table 19.7) and later included in regression models as a binary predictor of either affirming/misgendering-deadnaming tweets.

**Table 19.3:** SpaCy-lemmatized items for each of the eight lexical categories.

| Category | Count | Lemmas |
|---|---|---|
| Biological essentialism | 22 | science, biological, surgeon, surgery, chest, penis, ball, pussy, tit, dick, chromosome, implants, vagina, implant, boob, breast, tuck, surgically, mutilate, remove, operation |
| Pride/support | 16 | proud, pride, support, happy, joy, celebrate, beautiful, gorgeous, amazing, love, happy, congrat, congratulation, equality, confidence, respect |
| Coming-out event | 16 | come, revealing, reveal, announce, journey, formerly, transition, change, declare, identi-fie, identify, unveil, identity, embrace, introduce, news |
| Hate speech | 14 | faggot, ill, psychotic, mental, delusional, disturb, crazy, tranny, bizarre, fag, disorder, disgusting, transvestite, bitch |
| Transgender identity | 12 | transgender, trans, pronoun, non, binary, nonbinary, misgender, misgendere, misgender-ing, enby, nb, transphobic |
| Binary gender | 11 | woman, girl, male, female, man, boy, masculine, feminine, dude, chick, guy |
| LGBTQ+ | 7 | straight, lesbian, gay, sexuality, lgbt, lgbtq, queer |
| Gender/sex | 3 | gender, gendered, sex |

The results of these tests formed the basis for both the NAME and the PRONOUN binary regression models. Tweet- and user-level characteristics were also included. Additionally, to assess the interrelated nature of deadnaming and misgendering, NAME regression models included a continuous affirming pronoun rate measure while PRONOUN models included a continuous affirming name rate measure. To identify the clearest instances of misgendering/deadnaming and gender-affirmation, tweets that had a “mixed” usage rate (both misgendering/deadnaming and gender-affirming tokens) were excluded from analysis. For both the NAME and PRONOUN models, we aggregated celebrity data by identity/pronoun group: trans-binary, trans-nonbinary, cisgender, and Cox. To combine the data sets used in regression, we recorded the number of observations from the smaller data set and randomly sampled the same number from the larger data set. For example, in the trans-binary model, we recorded the total number of observations for Page (N=16,248) and randomly sampled the same number for Jenner (the larger data set).

# 4 Results

We present the distributional data descriptively, in tables of means, box plots, and line charts, before turning to regression models in the lexical analysis. Data in the NAME results comprise N=2,504,145 tweets at the NOM filter level from the Jenner and Page corpora. Data in the PRONOUN results comprise N=527,469 tweets at the ALTHAND filter level from all celebrity corpora. These data are separated chronologically in reference to each target celebrity's coming-out event (COE). PRE data consists of all tweets published before the first mention of the COE, POST data consists of the first mention and all tweets thereafter, and TOTAL data includes all tweets from the data collection period.

## 4.1 Distributional results

NAME results, which analyzed tweets from the NOM filter level (where all tweets contain names), indicate that Twitter users adopt Caitlyn Jenner and Elliot Page's gender affirming names almost instantaneously. In the first week following her coming-out event – week 0 in Figure 19.1 – 68.63% of tweets nominally affirmed Caitlyn Jenner, though this measure rose to 78.33% by the second week. Meanwhile, in the entire POST-COE period, 80.63% of tweets used Caitlyn Jenner's affirming name. For Elliot Page, the first week (86.69% affirming usage) was in fact slightly higher than the POST-COE period as a whole (84.3%). NAME data were also submitted to Automated Dickey-Fuller (ADF) tests, which test for statistically significant effects of time. These results suggest that there was a significant effect of time on the uptake of gender-affirming names across the entire analysis period.[9] It is important to note that the affirming name rate for the comparison celebrities, who never publicly asserted a new name, is 100% by definition. While people of course misname and/or nickname these comparison celebrities, these speech acts

9 Jenner: non-stationarity in TOTAL ($t$: -1.76, $\tau3$: -3.96), stationarity in PRE ($t$: -4.29, $\tau3$: -3.99, CI≤0.01), stationarity in POST ($t$: -4.22, $\tau3$: -3.98, CI≤0.01). Page: non-stationarity in TOTAL ($t$: -1.64, $\tau3$: -3.98), stationarity in PRE ($t$: -3.44, $\tau3$: -3.44, CI≤0.05), stationarity in POST ($t$: -4.92, $\tau3$: -3.98, CI≤0.01).

fundamentally differ from the gender dissonance and identity rejection introduced through the use of a deadname.

Table 19.4 shows that the percentage of deadnaming tweets POST-COE was remarkably similar for Page and Jenner. As expected, deadnaming rates in the weeks leading up to their COEs were near or at 0. Any nonzero name rate measure from this period resulted from Twitter user speculation or noise, as confirmed by hand.

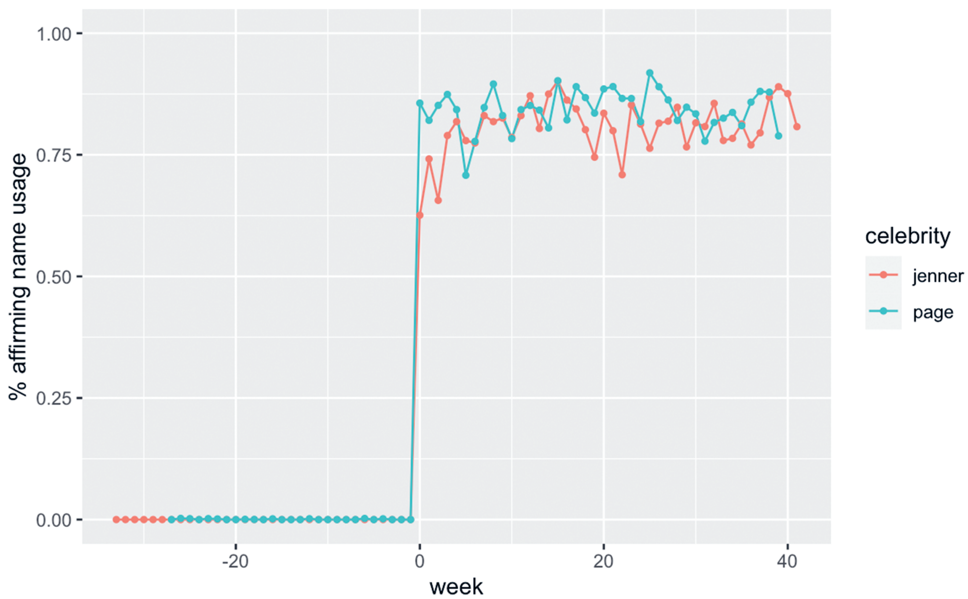


**Figure 19.1:** Affirming name uptake for trans-binary celebrities across the entire analysis period, with 0 representing the first week of tweets immediately after the coming-out event.

**Table 19.4:** Affirming name rate descriptive statistics for trans-binary celebrities in PRE-COE and POST-COE conditions.

| | PRE | | | POST | | |
|---|---|---|---|---|---|---|
| | **Weeks** | **Mean** | **S.E.** | **Weeks** | **Mean** | **S.E.** |
| **Jenner** | 31 | 2.6E-06 | 1.05E-05 | 41 | 0.80633 | 0.05606 |
| **Page** | 26 | 0.00058 | 0.00088 | 39 | 0.84301 | 0.04109 |
| **Average** | | 2.9E-04 | 4.43E-04 | | 0.82467 | 0.04858 |

PRONOUN results, which analyzed tweets from the ALTHAND filter level (most selective), indicate that, like the uptake of affirming names, Twitter users adopted the target celebrities' listed pronoun suites almost instantaneously after the COEs

(Figure 19.2). Table 19.5 displays descriptive statistics for the target celebrities across the POST, PRE, and TOTAL conditions. The affirming pronoun rate for week 0 was in fact higher than the POST-COE average for Smith (week0: 71.41%, POST-COE: 45.72%), Lovato (week0: 64.52%, POST-COE: 62.90%), and Page (week0: 92.24%, POST-COE: 85.89%).


**Figure 19.2:** Affirming pronoun uptake for target celebrities across the entire analysis period, with week 0 representing the coming-out event.

PRONOUN data for all seven celebrities were also submitted to ADF tests. These results indicated a significant effect of time on affirming pronoun uptake across the entire analysis period for all four target celebrities.[10] However, there was no similar effect of time in any of the comparison celebrities' data.[11] And while we observed stationarity in the data preceding the target celebrities' COEs, which coheres with our expectation, we were surprised to discover stationarity in the data *following* the COEs as well.[12] This suggests that the impact of a gradual "uptake period,"

**10** Smith (*t*: -2.21, $\tau$3: -3.98), Lovato (*t*: -2.32, $\tau$3: -3.98), Jenner (*t*: -2.27, $\tau$3: -3.96), Page (*t*: -1.51, $\tau$3: -3.98).

**11** Cox (*t*: -16.53, $\tau$3: -3.96, CI≤0.01), Doja (*t*: -6.56, $\tau$3: -3.99, CI≤0.01), Holland (*t*: -4.31, $\tau$3: -3.99, CI≤0.01).

**12** PRE-COE: Smith (*t*: -7.69, $\tau$3: -3.99, CI≤0.01), Lovato (*t*: -6.02, $\tau$3: -3.99, CI≤0.01), Jenner (*t*: -7.34, $\tau$3: -3.99, CI≤0.01), Page (*t*: -3.44, $\tau$3: -3.43, CI≤0.05). POST-COE: (*t*: -6.06, $\tau$3: -3.98, CI≤0.01), Lovato (*t*: -7.88, $\tau$3: -3.98, CI≤0.01), Jenner (*t*: -5.25, $\tau$3: -3.98, CI≤0.01), Page (*t*: -10.99, $\tau$3: -3.98, CI≤0.01).

where affirming pronoun usage slowly increases as the time since COE extends, is relatively minimal. In other words, it appears that pronoun uptake occurred virtually immediately after each target celebrity's COE.

Table 19.6 displays descriptive statistics for the comparison celebrities across the entire analysis period. While the trans-binary celebrities' pronouns were affirmed around 10% less frequently than the comparison celebrities, averaging to 81.85%, more than half of the pronouns in the POST conditions misgender Smith and only slightly less than half misgender Lovato. We also find lower standard deviations for the cisgender comparison celebrities than for Cox and the target celebrities (Tables 19.5 and 19.6), for whom the greater standard deviation values reflect variation in the frequency of misgendering.

**Table 19.5:** Affirming pronoun rate descriptive statistics for target celebrities in PRE-COE and POST-COE conditions.

| | | **PRE** | | | **POST** | | |
|---|---|---|---|---|---|---|---|
| **Celebrity** | **Pronouns** | **Weeks** | **Mean** | **S.E.** | **Weeks** | **Mean** | **S.E.** |
| **Trans-nonbinary** | | | | | | | |
| **Smith** | they/them | 26 | 0.15660 | 0.04493 | 39 | 0.45716 | 0.09605 |
| **Lovato** | they/them | 26 | 0.16025 | 0.06449 | 39 | 0.62900 | 0.07665 |
| **Average** | | | 0.15842 | 0.05471 | | 0.54308 | 0.08635 |
| **Trans-binary** | | | | | | | |
| **Jenner** | she/her | 31 | 0.08033 | 0.06573 | 41 | 0.77823 | 0.08659 |
| **Page** | he/they | 26 | 0.06805 | 0.06761 | 39 | 0.85886 | 0.06115 |
| **Average** | | | 0.07419 | 0.06667 | | 0.81854 | 0.07387 |
| **Total average** | | | 0.11631 | 0.06069 | | 0.68081 | 0.08011 |

**Table 19.6:** Affirming pronoun rate descriptive statistics for comparison celebrities across the entire analysis period.

| **Celebrity** | **Pronouns** | **Weeks** | **Mean** | **S.E.** |
|---|---|---|---|---|
| Transgender | | | | |
| Cox | she/her | 104 | 0.95523 | 0.06347 |
| Cisgender | | | | |
| Doja | she/her | 27 | 0.91360 | 0.02239 |
| Holland | he/him | 27 | 0.94092 | 0.03422 |
| Average | | | 0.92726 | 0.02826 |

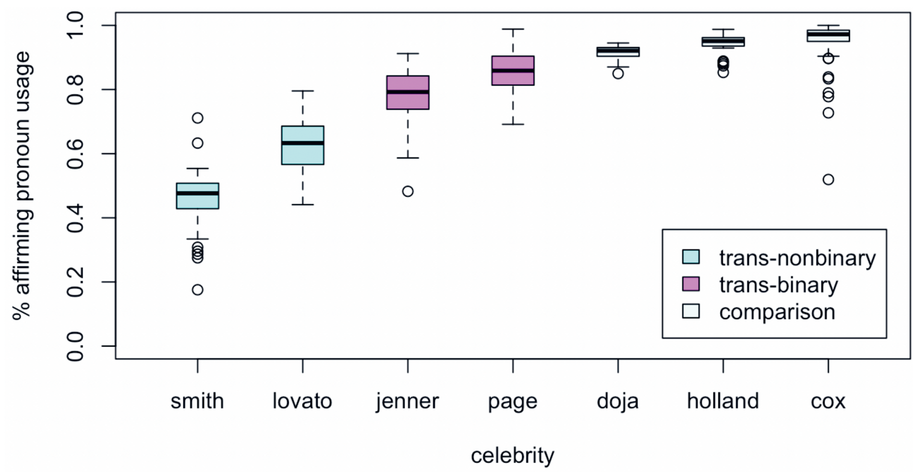


**Figure 19.3:** Mean affirming pronoun rate by week for all celebrities. Data for comparison celebrities spans the entire analysis period, while data for target celebrities is POST-COE.

## 4.2 Lexical results

Figure 19.5 displays the results from the PRONOUN binary logistic regression for the target celebrities, separated by pronoun group, as well as Cox. All lexical categories beside LGBTQ+ terms significantly predicted whether a tweet would misgender or affirm the trans-binary celebrity under discussion. Meanwhile, the LGBTQ+ terms category was also a significant predictor for the trans-nonbinary data. For the trans-binary celebrities, the strongest significant binary predictor of gender-affirming tweets was the presence of pronouns in the user's bio ($\beta$=1.10367, $p<0.001$) while the strongest binary predictor of misgendering tweets was the presence of binary gender terms in the tweet ($\beta$=-0.72769, $p<0.001$). Meanwhile, the strongest significant continuous predictor of gender-affirming tweets was the rate at which the tweet used the celebrity's gender affirming name ($\beta$=1.32884, $p<0.001$).

Furthermore, tweets written by users with either LGBTQ+ or transgender flags in their bio were significantly more likely to use the celebrity's affirming pronoun suite ($\beta$=0.82470, $p\leq0.001$).).

For the trans-nonbinary celebrities, PRONOUN regression results somewhat differ. The strongest significant binary predictor of gender-affirming tweets by far was the presence of transgender terms ($\beta$=1.45482, $p<0.001$) while the strongest binary predictor of misgendering tweets was also the presence of binary gender terms in the tweet ($\beta$=- 0.93170, $p<0.001$). Furthermore, tweets written by users with either listed pronouns ($\beta$=1.29515, $p<0.001$) or at least one of the pride flags

($\beta$=0.27425, $p$<0.01) present in their bio were significantly more likely to use gender-affirming pronouns.

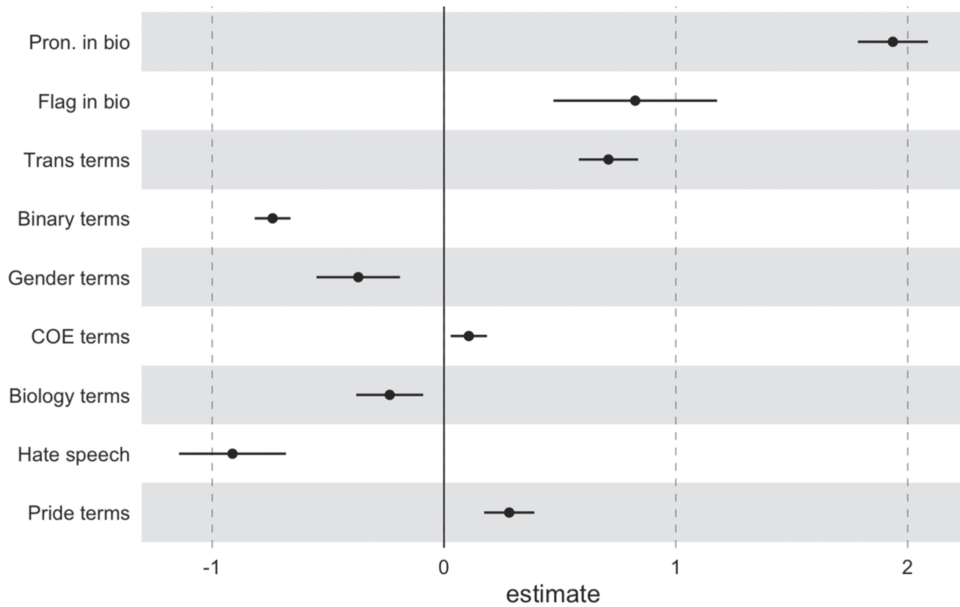


**Figure 19.4:** Effect of significant (p-value≤0.05) binary measures on (dead)name usage for trans-binary group. Positive coefficients represent tweets that were more likely to affirm, while negative coefficients represent those more likely to misgender.

For Cox, who is a transgender woman *without* a publicly-documented COE, significant effects of transgender terms ($\beta$=0.41072, $p$<0.05), binary gender terms ($\beta$=-0.45536, $p$<0.001), pride terms ($\beta$=0.55919, $p$<0.001), COE terms ($\beta$=0.42141, $p$<0.01), and pronouns in bio ($\beta$=0.63079, $p$<0.001) pattern with the target celebrities. The strongest significant predictor of gender-affirming tweets was, like the trans-binary celebrities, the presence of pronouns in the user's bio. However, the effects of gender/sex terms, biological essentialism terms, hate speech terms, and flags in bio did not reach significance.

For Holland and Doja, who are cisgender and do not have publicly-documented COEs, only two lexical effects and one user-level effect reached significance. While binary gender terms significantly predicted misgendering for the target celebrities and Cox, these terms significantly predicted gender-affirming (coreferentially accurate) tweets in the cisgender model (β=0.35856, S.E.= 0.06483, p≤0.001). This result coheres with our expectation – binary gender terms are likely to be used when discussing cisgender binary celebrities – and increases our confidence in the binary gender terms finding for the other celebrities. There was also a significant effect of pride terms (β=0.66642, S.E.= 0.07976, p≤0.001), which suggests that our filtering process may have introduced bias towards gender-affirming tweets that express positive sentiment. Nevertheless, the effect of pride terms is larger in the trans-binary model (β=0.91315). Finally, the pronouns in bio flag was a significant predictor of misgendering (coreferentially inaccurate) tweets (β=0.32300, S.E.= 0.03863, p≤0.001). By hand analysis revealed Twitter user homophily as one possible explanation for this result: many of the tweets tagged as misgendering were in fact quoting Doja Cat lyrics, suggesting that Dojo Cat's fanbase may be more likely to both have pronouns in their bio and quote Dojo's *he*-suite inflected lyrics.

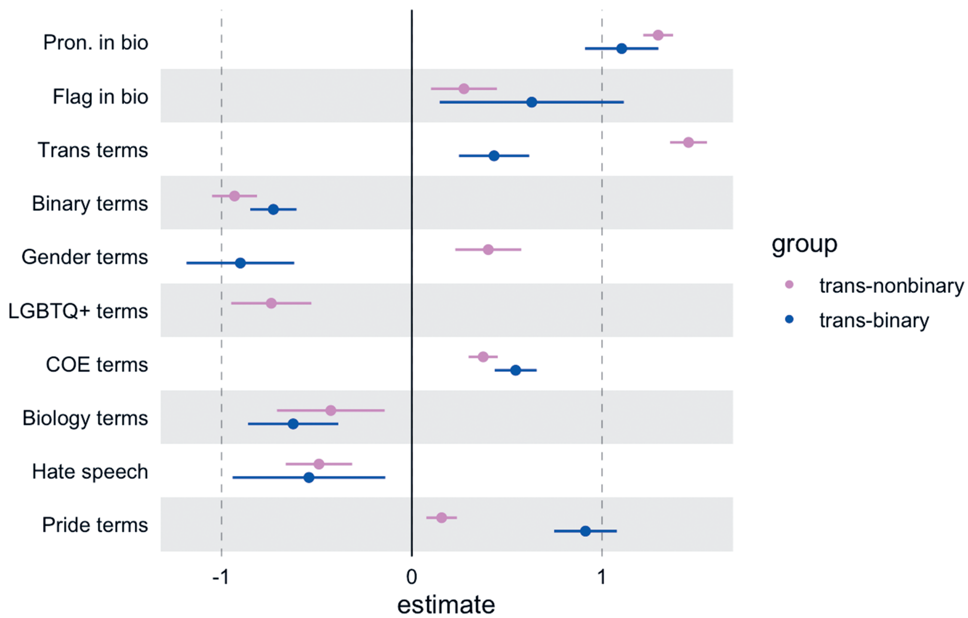


**Figure 19.5:** Effect of significant (p-value≤0.05) binary measures on gendered pronominal usage among target groups. Positive coefficients represent tweets that were more likely to affirm, while negative coefficients represent those more likely to misgender.

## 5 Discussion

For the transgender participants in Zimman (2009), their coming-out event (COE) was achieved through the declaration that their social gender identity matched their internal experience of gender. The presentation of new pronoun suites and/or names as part of these events are not simply "changes" but assertions – ones that contest antigender ideologies that dehumanize transgender people. Still, the dissemination of these speech acts precipitates sociopragmatic variation that is in part driving ongoing change in the pronoun system of English (Conrod, 2022). Gender identities are in part constituted through the variable responses of interlocutors, who can use language to reject or ratify transgender assertions of gender (Bucholtz & Hall, 2004; Zimman, 2017).

The present study demonstrates that these assertions are taken up by Twitter users almost immediately, but that misgendering/deadnaming remain present and largely stable thereafter. Through our distributional results, we show that there was no significant effect of time on rates of affirming name or pronoun usage after Caitlyn Jenner, Elliot Page, Sam Smith, and Demi Lovato came out. The average rate of affirming pronoun usage for the first seven days following their COE was even higher than the average rate across the 9 month analysis period for Page, Smith, and Lovato. That functional-class change occurs practically instantaneously is remarkable, and speaks to the potency of changing gender notions in mediating systematic linguistic change (Conrod 2019b).

For Jenner, meanwhile, the first week featured much lower affirming usage rates (PRON: 61.1%; NAME: 68.63%) than the entire post-COE analysis period (PRON: 77.82%; NAME: 80.63%). This is perhaps the result of historical time, as Jenner came out in one of the biggest media events of the 2010s, nearly four years before any of the other target celebrities. In fact, we observed higher affirming pronoun rates for the celebrity with the chronologically later COE in both the trans-binary and trans-nonbinary pairs. This suggests that social shifts surrounding gender may be trending towards more gender-affirming language usage on a large scale (Zimman 2020).

Our results illustrate that gender-affirming pronoun usage was significantly predicted by affirming name usage, and vice versa, for the trans-binary celebrities. This pattern is likely related to a gender expectancy effect (Doherty & Conklin, 2017), whereby users who are already using an affirming nominal form are more likely to use the pronominal form that matches their lexical entry for that name. In other words, users who are already misgendering/deadnaming or affirming have a greater tendency to assume and assign the (pro)nominal form that makes the coreferential relationships cohere in terms of gender (McConnell-Ginet 2003).

Gender-affirming (pro)nominal usage was also significantly predicted by the presence of transgender, COE, or pride terms in the tweet, as well as listed pronouns or LGBTQ+ pride flags in the Twitter user's profile. The user demographic findings are unsurprising: when an individual lists their pronouns, they promote an understanding that gender identity cannot be assumed or assigned. Similarly, the inclusion of a transgender or LGBTQ+ pride flag suggests allyship or, more likely, membership within these communities. The lexical findings mirror recent research on nonbinary *they*, which has found that transgender people and those with greater awareness of transgender issues are more likely to accept nonbinary *they* (Ackerman 2018; Camilliere et al. 2021; Conrod 2019b; Hekanaho 2020). The significance of transgender, COE, and pride terms illustrates that many of the affirming tweets in our data were written by users who have a vested interest in celebrating lived transgender identities. More precisely, language users who are more invested in supporting the assertions made through the target celebrities' COEs are more likely to modify their lexical entries (in the trans-binary case) or adopt linguistic innovations (trans-nonbinary) in order to ratify them.

However, we also observed considerable differences within the target celebrities in the size and direction of binary lexical effects predicting affirming pronoun usage (Figure 19.5). While the presence of *gender* and *sex* strongly predicted misgendering for the trans-binary celebrities, it significantly predicted affirming usage for the trans-nonbinary celebrities. Additionally, the effect size for transgender terms was much larger for the trans-nonbinary celebrities – the single greatest predictor, in fact – than for the trans-binary celebrities. Considering the overall lower usage of nonbinary *they*, it appears that trans-nonbinary gender affirming tweets depend more heavily on the presence of transgender identity and gender terms to successfully elicit nonbinary *they*. In other words, the nonbinary identities of Smith and Lovato are more likely to be linguistically ratified when the user simultaneously recognizes their rejection of the gender binary. Meanwhile, the opposite effect of gender terms for Page and Jenner suggest that, for language users who misgender them, their transgender identities are directly at odds with notions of sex and gender.

The observation that gender-affirming (pro)nominal uptake occurred immediately and remained stable post-COE entails that misgendering/deadnaming persisted as well. We uncovered significant disparities in the extent to which the seven celebrities were misgendered that accord with differences in listed pronoun suite and identity (Figure 19.3). Post-COE, 45.69% of tweets misgender the trans-nonbinary celebrities who list *they*, while 18.15% of tweets misgender their trans-binary counterparts, Jenner and Page, who list *she* and *he*, respectively. Furthermore, Jenner and Page are deadnamed at about the same rate (17.5% of tweets) at which they are misgendered. Given that the celebrity misgendered more in each pair came out earlier in historical time, shifting sociocultural attitudes surrounding pronoun and name usage as part of gender identity may partially explain these disparities. And while transmisogyny could in part explain why Jenner was ultimately misgendered and deadnamed more than Page, this pattern does not extend to the trans-nonbinary pair. Ultimately, the disparities between the comparison and target celebrities demonstrate how Twitter's 2018 ban on "dehumanizing speech," including the “targeted misgendering or deadnaming of transgender individuals,” has evidently failed (Robertson 2018).

The disparities we observe within the target group follow previous production work on nonbinary *they*, which found that *they* is used at much lower rates than the binary pronouns *she* or *he* in written discussions of transgender individuals when controlling for gender identity (Arnold, Marquez, Li, & Franck 2022). However, we also show that the comparison celebrities are misgendered less (7.27% of tweets) than the target celebrities as a whole. The comparison celebrities comprise Tom Holland and Doja Cat, for whom, as cisgender celebrities, misgendering is primarily the result of noise in the data, and Laverne Cox, who is transgender but does not have a publicly-documented COE. That Cox is misgendered so much less than the other transgender celebrities suggests that the historical time in which the COE occurs, as well as the relative prominence of the COE itself – especially among celebrities – may influence the extent to which transgender people are misgendered/deadnamed.

**Table 19.7:** Example lexically-tagged deadnaming tweets from the Page corpus.

| **Biology** | ***Binary*** | **Hate** | **~~Gender~~** | **Raw Tweet Text** |
|---|---|---|---|---|
| 1 | 1 | 3 | 0 | Ellen Page is a mentally ill *woman* who **mutilated** her body. And this disturbed individual is a role model for the left. . . I really sucks being witness to societal decay of this magnitude. God save America. |
| 2 | 4 | 0 | 1 | There are only 2 ~~genders~~, only *women* can have kids. *men* who think they are *girls* need to see a shrink. Ellen Page is still a *girl* she just needs **breast implants** now |

For the target celebrities, misgendering/deadnaming tweets were significantly predicted by binary gender, biological essentialism, and hate speech terms, as qualitatively illustrated in Table 19.7. The use of binary gender terms reflect a theory of gender that presupposes a strict and rigid gender binary (Borba 2022), punishing those who transgress it. Such attitudes have been found to predict lower acceptance of nonbinary *they* (Bradley et al. 2019). Similarly, the biological essentialism terms show how users subjugate these celebrities’ bodies in comparison to biologically “natural” men and women, echoing work on deadnaming within online platforms (Turton 2021). Lastly, the prevalence of hate speech epitomizes how misgendering and deadnaming can dehumanize transgender people (Mendelsohn et al. 2020), with critical implications for public health and safety (Johnson et al. 2019; McLemore 2015).

## 6 Limitations

This study suffered from several limitations, mainly arising from coreference resolution with social media data. Despite several rounds of filtering, thousands of irrelevant tweets slipped through and potentially biased both the distributional and lexical results. It is also unfortunate that our decision to exclude pronouns that were never part of Jenner or Cox's self-presentation removed instances of harmful *they*-misgendering from our data set and, therefore, also excluded consideration of this form of misgendering from our analysis.

Quantitative methods, particularly when applied to large amounts of data, are inherently reductive; they require researchers to implement categories and, often, to binarize socially meaningful data that is otherwise contextualized, fluid, and nuanced. We acknowledge the shortcomings that arise when researchers reduce identity and speech acts to discrete quantitative data but also suggest that these tradeoffs can elicit valuable and complementary large-scale perspectives on linguistic behavior and social change over time. Finally, while a transgender man without a documented COE would have completed the target-comparison design nicely, we were unable to identify one such sufficiently popular celebrity at the time of analysis.

## 7 Conclusion

We present the first large-scale study on the usage of names and pronouns in reference to transgender people. Through a computational analysis of Twitter data we find that language users almost instantly adopt gender-affirming (pro)nominals merely days after prominent transgender celebrities come out. At the same time, we illustrate ties between ongoing culture wars over "gender ideology" and systematic linguistic behavior, showing that tweet-level lexical content and user-level identifiers can predict misgendering and deadnaming as well as gender-affirming usages.

Further, our lexical results differ between transgender celebrities who list binary pronouns and those who list nonbinary *they*, a sign that future work should take care to disaggregate transgender individuals based on self-asserted gender identity. We also highlight in particular widespread misgendering/deadnaming on Twitter, one of the most popular social media platforms, that accompanies dehumanizing hate speech. Given the critical importance of affirming name and pronoun usage in ratifying transgender identities, these findings offer a foundation off which future research can further explore the sociopragmatic factors conditioning the uptake of gender-affirming language.

# References

Ackerman, Lauren. 2018. Our words matter: acceptability, grammaticality, and ethics of research on singular ’they’-type pronouns. Newcastle University. Newcastle upon Tyne: Newcastle University dissertation.

Ackerman, Lauren. 2019. Syntactic and cognitive issues in investigating gendered coreference. *Glossa: a journal of general linguistics* 4(1). https://doi.org/10.5334/gjgl.721

Arnold, E. Jennifer, Attire Marquez, Jiefang Li & Genevieve Franck. 2022. Does nonbinary they inherit the binary pronoun production system? *Glossa Psycholinguistics* 1(1). https://doi.org/10.5070/G601183

Borba, Rodrigo. 2022. Enregistering “gender ideology”: The emergence and circulation of a transnational anti-gender language. *Journal of Language and Sexuality* 11(1). 57–79.

Bradley, D. Evan D, Julia Salkind, Ally Moore & Sofi Teitsort. 2019. Singular ‘they’ and novel pronouns: gender-neutral, nonbinary, or both? *Proceedings of the Linguistic Society of America* 4(1). https://doi.org/10.3765/plsa.v4i1.4542

Bucholtz, Mary & Kira Hall. 2004. Theorizing identity in language and sexuality research. *Language in Society* 33(4). 469–515.

Camilliere, Sadie, Amanda Izes, Olivia Leventhal & Daniel J. Grodner 2021. They is changing: Pragmatic and grammatical factors that license singular they. *Proceedings of the Annual Meeting of the Cognitive Science Society* 43. 1542–1548.

Conrod, Kirby. 2018. Pronouns and misgendering*.* Paper presented at New Ways of Analyzing Variation 47, New York University, October 18–21, 2018.

Conrod, Kirby. 2019a. Names before pronouns: Variation in pronominal reference and gender. In Daniel K. E. Reisinger (ed.), *Proceedings of Northwest Linguistics Conference 33. Vancouver, British Columbia, Canada, 2019,* 15–26. Vancouver: University of British Columbia Working Papers in Linguistics.

Conrod, Kirby. 2019b. *Pronouns raising and emerging.* Seattle: University of Washington dissertation.

Conrod, Kirby. 2020. Pronouns and gender in language. In Kira Hall & Rusty Barrett (eds.), *The Oxford Handbook of Language and Sexuality*. Oxford: Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190212926.013.63

Conrod, Kirby. 2022. Variation in English gendered pronouns: Analysis and recommendations for ethics in linguistics. *Journal of Language and Sexuality* 11(2). 141–164.

Darwin, Helena. 2017. Doing gender beyond the binary: A virtual ethnography. *Symbolic Interaction* 40(3). https://doi.org/10.1002/symb.316

Dickey, A. David & Wayne A. Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association* 74(366a). https://doi.org/10.1080/01621459.1979.10482531

Doherty, Alice, & Kathy Conklin. 2017. How gender-expectancy affects the processing of “them”. *Quarterly Journal of Experimental Psychology* 70(4)*.* https://doi.org/10.1080/17470218.2016.1154582

GLAAD. 2021. “Elliot page, Oscar-nominated star of Umbrella Academy, speaks out about being transgender.” https://www.glaad.org/blog/elliot-page-oscar-nominated-star -umbrella-academy-speaks-out-about-being-transgender (accessed 15 March 2022).

Haslam, Nick. 2006. Dehumanization: An integrative review. *Personality and Social Psychology Review* 10(3)*.* https://doi.org/10.1207/s15327957pspr1003_4

Hekanaho, Laura. 2020. *Generic and nonbinary pronouns: Usage acceptability and attitudes.* Helsinki: University of Helsinki dissertation.

Johnson, Kelly, Allen J. LeBlanc, Julianna Deardorff & Walter O. Bockting. 2019. Invalidation experiences and protective factors among non-binary adolescents. *Journal of Adolescent Health* 57(2). https://doi.org/10.1080/00224499.2019.1608422

Jones, J. Jason. 2021. A dataset for the study of identity at scale: Annual prevalence of American Twitter users with specified token in their profile bio 2015–2020. *PloS ONE* 16(11). https://doi.org/10.1371/journal.pone.0260185

Konnelly, Lex & Elizabeth Cowper. 2020. Gender diversity and morphosyntax: An account of singular they. *Glossa: a journal of general linguistics* 5(1). https://doi.org/10.5334/GJGL.1000

McConnell-Ginet, Sally. 2003. "What's in a name?" Social labeling and gender practices. In Janet Holmes & Miriam Meyerhoff (eds.), *The Handbook of Language and Gender*, 69–97. Oxford: Blackwell Publishings Ltd.

McConnell-Ginet, Sally. 2015. Gender and its relation to sex: The myth of 'natural' gender. In Greville G. Corbett (ed.), *The Expression of Gender*, 3–38. Berlin/Boston: De Gruyter Mouton.

McLemore, Kevin A. 2015. Experiences with misgendering: Identity misclassification of transgender spectrum individuals. *Self and Identity* 14(1). https://doi.org/10.1080/15298868.2014.950691

Mendelsohn, Julia, Yulia Tsvetkov & Dan Jurafsky. 2020. A framework for the computational linguistic analysis of dehumanization. *Frontiers in Artificial Intelligence* 3. https://doi.org/10.3389/frai.2020.00055

Monroe, L. Burt, Michael P. Colaresi & Kevin M. Quinn. 2008. Fightin' words: Lexical feature selection and evaluation for identifying the content of political conflict. *Political Analysis* 16(4). https://doi.org/10.1093/pan/mpn018

Morton, S. Thomas. 2000. Coreference for NLP applications. In *Proceedings of the 38th annual meeting of the association for computational linguistics, Hong Kong, 2000,* 173–180. Boston: Association for Computational Linguistics.

Nguyen, Dong, Seza A. Doğruöz, Carolyn p. Rosé & Franciska de Jong. 2016. Computational Linguistics: A survey. *Computational Linguistics* 42(3). https:doi.org/10.1162/COLI_a_00258

Robertson, Adi. 2018. November 27. Twitter has banned misgendering or 'deadnaming' transgender people. *The Verge*. https://www.theverge.com/2018/11/27/18113344/twitter-trans-user-hateful-content-misgendering-deadnaming-ban

Russell, T. Stephen, Amanda M. Pollitt, Gu Li & Arnold H. Grossman. 2018. Chosen name use is linked to reduced depressive symptoms, suicidal ideation, and suicidal behavior among transgender youth. *Journal of Adolescent Health* 63(4). https:doi.org/10.1016/j.jadohealth.2018.02.003

Turton, Stephen. 2021. Deadnaming as disformative utterance: The redefinition of trans womanhood on Urban Dictionary. *Gender and Language* 15(1). https:doi.org/10.1558/genl.18816

Valentine, E. Sarah & Jillian C. Shipherd. 2018. A systematic review of social stress and mental health among transgender and gender non-conforming people in the United States. *Clinical Psychology Review* 66(1). https:doi.org/10.1016/j.cpr.2018.03.003

Zimman, Lal. 2009. 'The other kind of coming out': Transgender people and the coming out narrative genre. *Gender & Language* 3(1). 53–80.

Zimman, Lal. 2017. Transgender language reform. *Journal of Language and Discrimination* 1. 84–105.

Zimman, Lal. 2020. Transgender language, transgender moment: Toward a trans linguistics. In Kira Hall & Rusty Barrett (eds.), *The Oxford Handbook of Language and Sexuality*. Oxford: Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190212926.013.45