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Popular music lyrics and musicians' gender over time: A computational approach

The present study investigated how the gender distribution of the United Kingdom's most popular artists has changed over time and the extent to which these changes might relate to popular music lyrics. Using data mining and machine learning techniques, we analysed all songs that reached the UK weekly top 5 sales charts from 1960 to 2015 (4,222 songs). DICTION software facilitated a computerised analysis of the lyrics, measuring a total of 36 lyrical variables per song. Results showed a significant inequality in gender representation on the charts. However, the presence of female musicians increased significantly over the time span. The most critical inflection points leading to changes in the prevalence of female musicians were in 1968, 1976, and 1984. Linear mixed-effect models showed that the total number of words and the use of self-reference in popular music lyrics changed significantly as a function of musicians' gender distribution over time, and particularly around the three critical inflection points identified. Irrespective of gender, there was a significant trend towards increasing repetition in the lyrics over time. Results are discussed in terms of the potential advantages of using machine learning techniques to study naturalistic singles sales charts data.

Keywords: popular music, lyrics, gender, DICTION, sales charts, machine learning.

Introduction

Popular music is a cultural product, an artefact of society that reflects people's preferences, values, and psychological traits (DeWall, Pond, Campbell, & Twenge, 2011; Pettijohn & Sacco, 2009). As such, a critical study of popular music can provide valuable insights into different aspects of society at a specific point in time. Research suggests that listeners' music preferences are a representation of their personality, cognitive styles, attitudes, and personal values (see Greasley & Lamont, 2016, for a review). Thus, by investigating properties of popular music (e.g., lyrics) and characteristics of the artists (e.g., gender), one could identify general attributes of the sociocultural context in which the music was produced and consumed.

Since the beginning of the modern music industry, top artists in the singles sales charts have been predominantly male (Dukes, Bisel, Borega, Lobato, & Owens, 2003; Hesbacher, Clasby, Clasby, & Berger, 1977; Lafrance, Worcester, & Burns, 2011; Wells, 1986, 1991, 2001). For example, Wells (1986) found that female artists were significantly underrepresented in US popular music from 1955 to 1984, accounting for approximately 10 of Billboard's top 50 singles per year since 1955; and Lafrance et al. (2011) showed that artists in the Billboard top 40 charts between 1997 and 2007 continued to be predominantly male. In addition to American sales charts, Wells (1991) examined the success of female artists in the UK specifically. The peak year for female artists in the UK was 1985 (17 hits out of the year's top 40 singles), followed by 1987 (15 hits), and 1986 (14 hits), indicating that in the mid 1980s female success rates in UK were higher than in earlier periods. Therefore, two main conclusions can be drawn from this body of research: top artists in the singles sales charts have been predominantly male, but the presence of female artists among rank orderings of the most successful musicians may increase over time and seem to indicate critical points of change.

To the best of our knowledge, Dukes et al.'s (2003) study covered the most extensive time period (40 years, from 1958 to 1998) while focusing on musicians' gender. The authors found associations between musicians' gender and specific lyrical themes, with the specific nature of the themes changing, depending on the period. For instance, from 1976 to 1984, female artists used five times more sexual references in lyrics than did males, but from 1991 to 1998, males used more sexual references. However, Dukes et al.'s (2003) dataset was limited, comprising only 100 songs. More recently, Author 2 & Author 3 (2017) investigated associations between the gender of musicians and the prevalence of specific lyrical themes, using a much larger dataset (4,534 observations) representing every song to have reached the United Kingdom's top 5 singles chart from 1960 to 2015. The authors also identified associations between musicians' gender and specific lyrical themes. For example, there was a positive relationship between the proportion of band members who were female and the use of words indicative of inspiration and negative relationships involving the use of words indicative of aggression and diversity (Author 2 & Author 3, 2017). Nevertheless, variations over time were not considered, and so the main motivation of the present study was to add consideration of time into their analyses.

In addition to the relationship between popular music and artists' gender, studies have considered changes in popular song lyrics over time, focusing on social, economic, and psychological changes in the USA (Christenson, Haan-Rietdijk, Roberts, & Bogt, 2018; DeWall, Pond, Campbell, & Twenger, 2011; McAuslan & Waung, 2016; Pettijohn & Sacco, 2009; Zullow, 1991), Germany (Ruth, 2018), and UK (Author 3, Author 2, Kane, & Sheridan, 2018). Despite finding a number of provocative results, these studies, did not consider the musicians' gender or potential associations between gender and the various lyrical variables of interest. This is particularly unfortunate given the clear interest in gender equality that has characterised a significant amount of public discourse from the 1960s onwards (e.g., Alvarez, 1990; Chant, 2011; Dollar & Gatti, 1999; Gundersen, 2011; Lorber, 2001; Jeffreys, 2013; Ridgeway, 2011).

Furthermore, there are a number of limitations to previous research that has addressed trends in music lyrics over time and the correlation between properties of the music and the gender of performers. These include that (1) most studies are based on a relatively small number of songs (≤ 1,000 songs) that enjoyed cultural prominence over a reasonably short period; (2) most studies have mainly focused on US culture and US popular music, overlooking whether trends are also present elsewhere; (3) studies have only looked at a very limited number of lyrical themes, with a particular focus on interpersonal relationships, so that we know little about other ways in which music lyrics and their relationship with gender have changed over time; and (4) most studies have used human coders to analyse the content of popular songs, limiting both the quantity of lyrics that can be analysed and the reliability and accuracy of the results. One of the motivations of the present study was to overcome the aforementioned limitations.

As part of a series of papers focusing on popular music lyrics in the UK (Author 3 et al., 2018; Author 2 & Author 3, 2017), the present study extends the scope to consider lyrical content, musicians' gender, and time within the same research design. The first aim was to investigate how the gender distribution of the UK's most popular musicians has changed over time. Based on previous literature on the role of female artists in popular music (e.g., Dukes et al., 2003; Lafrance et al., 2001; Wells, 1986, 1991, 2001), it was hypothesized that popular music in the United Kingdom would be characterized by a considerable gender inequality, although we expected a significant increase in the presence of female artists in more recent years. We also expected to find critical inflection points in which the prevalence of females increased considerably compared to earlier periods, although we could not hypothesize when these would occur. The second aim was to examine how popular music lyrics from the United Kingdom changed as function of musicians' gender over time. Due to the lack of published literature on this topic and the techniques used to analyse the dataset (i.e., classification trees and random forest models), this second analysis was exploratory and, therefore, no specific hypotheses were formulated.

Method

The dataset used in the present study is an adapted version of that used by Author 3 et al., (2018) and Author 2 and Author 3 (2017).

Data collection

All songs that reached the United Kingdom top 5 weekly sales charts from March 1960 to the end of December 2015 were included in the dataset. Chart information from 1960 to 1995 was obtained from Gambaccini, Rice, and Rice (1996), whereas the information from 1996 to 2015 was obtained from the official charts' website (www.officialcharts.com). This chart information is the same used by the British Broadcasting Corporation (BBC), representing the most widely recognised chart in the country. This chart information is based on sales of physical music media, and more recently also digital downloads and streaming. Songs were included at the year level: any song that reached a top 5 position in more than one year was included as pertaining to each year. In the present investigation, a total of 81 instrumental songs (did not contain words) and 11 songs that had ≤ 15 words were excluded. As a result, the final dataset employed a total of 4,671 observations representing 4,222 unique songs performed by 2,287 artists.

The lyrics were retrieved from several sources and each set was verified against a second source (see Author 2 and Author 3, 2017, for a more detailed description of how the lyrics were obtained and processed). Missing lyrics were reintroduced in cases of previously eliminated redundancies or repetitions (e.g., "Chorus x 2" was replaced with two instances of the chorus), ensuring that each text file contained the same lyrics as the recorded version; and word processor operations were used to extend contractions to their full representation (e.g., "it's" was replaced with "it is") and to correct misspellings (e.g., "wanna" was replaced with "want to").

Coding

Lyrical variables

As in Author 2 and Author 3 (2017) and Author 3 et al. (2018), DICTION 7.0 software (Hart et al., 2013) was used to conduct a computerised analysis of the lyrical content of the songs. DICTION has a built-in database consisting of 50,000 previously analysed texts. By analysing each given text against the normative database, the software calculates scores for 36 discrete "dictionaries" or lyrical variables (see Table 1). In the present study, we used the raw scores measured by DICTION's 'averaged' option, which calculates one set of scores for the entire text, regardless of length, generating the score for each 500-word unit and then averaging the scores out. This option is specifically designed for processing large number of texts of varying size and allows for a direct comparison between them.

Table 1. Summary of DICTION's lyrical variables (taken from Hart, 1997)

Lyrical Variable	Definition
Total words	The total number of words in a given text.
Numerical terms	Any sum, date or product. Each separate group of integers is treated as a single word.
Ambivalence	Words expressing hesitation or uncertainty.
Self-reference	Contains all first-person references.
Tenacity	All uses of the verb 'to be' (e.g., is, am, will, shall), three definitive verb forms (has, must, do), their variants, and all associated contractions (e.g., he'll, they've, ain't).
Levelling	Words used to ignore individual differences and to build a sense of completeness and assurance.
Collectives	Singular nouns connoting plurality that function to decrease specificity (e.g. social groupings, task groups such as the army, and geographical entities).
Praise	Affirmations of some person, group, or abstract entity.
Satisfaction	Terms associated with positive affective states.
Inspiration	Abstract virtues deserving of universal respect.
Blame	Terms designating social inappropriateness (e.g., naïve), evil, unfortunate circumstances, unplanned vicissitudes, and outright denigrations.
Hardship	Contains natural disasters, hostile actions, censurable human behaviour, unsavoury political outcomes, normal human fears and incapacities.
Aggression	Terms embracing human competition and forceful actions.
Accomplishment	Words expressing task completion and organized human behaviour.

Communication	Terms referring to social interaction.
Cognitive terms	Contains words referring to cerebral processes, both functional and imaginative.
Passivity	Words ranging from neutrality to inactivity.
Spatial awareness	Terms referring to geographical entities, physical distances, and modes of measurement.
Familiarity	A selected number of Ogden's (1960) 'operation' words, which are considered to be the most common words in the English language.
Temporal awareness	Terms that fix a person, idea, or event within a specific time interval.
Present concern	A Selective list of common present-tense verbs concerning general physical activity, social operations, and task performance.
Human interest	Includes standard personal pronouns, family members and relations, and generic terms (e.g., a friend).
Concreteness	Words concerning tangibility and materiality.
Past concern	Past tense form of the verbs contained in the Present Concern dictionary.
Centrality	Terms denoting institutional regularities and/or substantive agreement on core values.
Rapport	Words denoting attitudinal similarities among people.
Cooperation	Words describing behavioural interactions among people that often result in a group product.
Diversity	Words describing individuals or groups of individuals differing from the norm.
Exclusion	Describes the sources and effects of social isolation.
Liberation	Includes terms describing the maximizing of individual choice and the rejection of social conventions.
Denial	Standard negative contractions (aren't), negative function words (nor), and terms designating null sets (nothing).
Motion	Terms connoting human movement, physical processes, journeys, speed, and transit.

Insistence	A measure of code restriction and semantic 'contentedness'. Includes all words occurring three or more times that function as nouns or noun-derived adjectives, and calculates (number of eligible words x sum of their occurrences) / 10.
Embellishment	Calculated as (praise + blame + 1) / (present concern + past concern + 1).
Variety	The number of different words divided by total number of words.
Complexity	Mean number of characters per word.

Musicians' gender

The gender of the musicians was coded as in Author 2 and Author 3 (2017). Coding was based on biographical sources (e.g., music industry web sites and music encyclopaedias) to create two specific variables for each song entry: the proportion of band members who were female ('band gender') and the proportion of singers who were female ('singer gender') calculated by dividing the total number of female members by the total number of members. Note that only named musicians listed as such during the year the song in question reached a top 5 chart position were included (excluding any recording studio staff, producers or other music industry professionals). For analysis, two datasets were created, in which those cases that had no information regarding the gender of the band or singer were excluded. The total number of observations in the band gender dataset was 4,604 and in the singer gender dataset 4,671.

Results

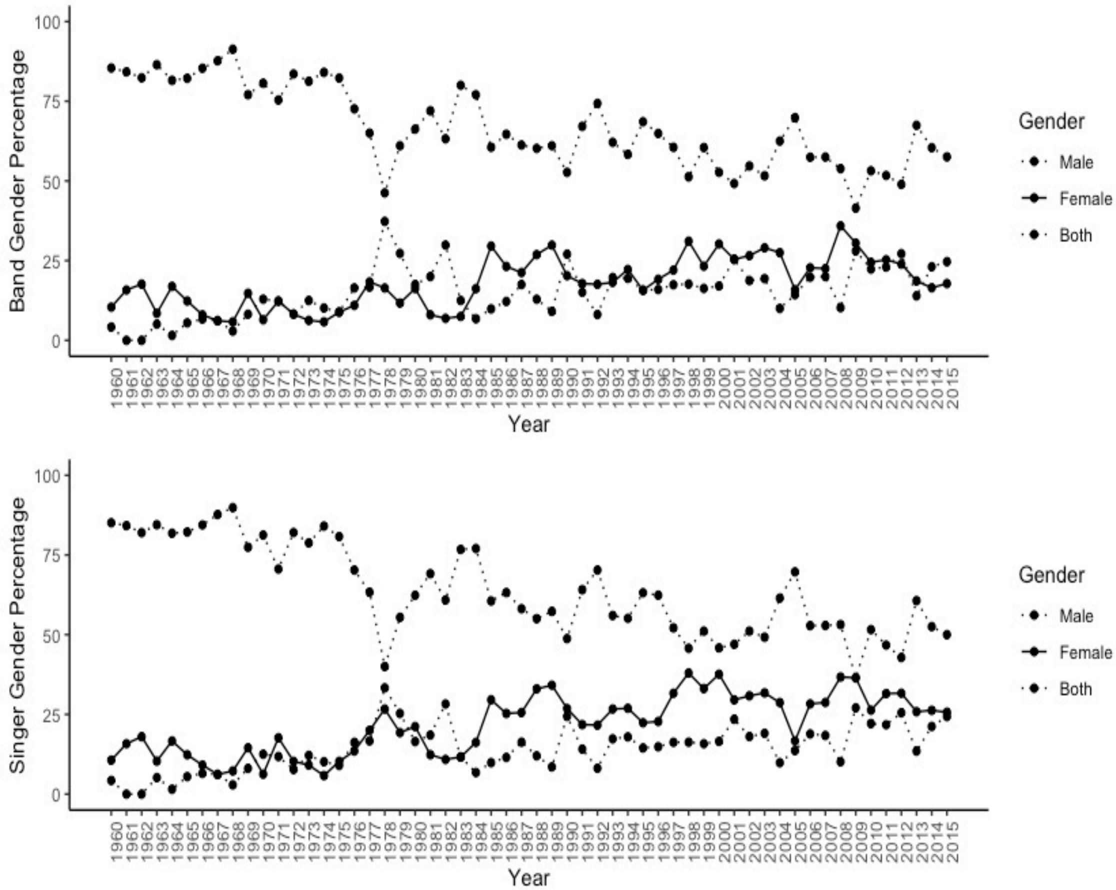
A three-step process was used to analyse the data. First, we examined the relationship between the gender of the artists and time (1960-2015), and identified critical inflection points in which the prevalence of female musicians changed significantly. Secondly, we identified the most relevant lyrical variables associated with changes in the distribution of band and singer gender. Finally, we examined whether the lyrical variables identified in the second step varied as a function of time and gender, focusing on those cases where the interaction term was statistically significant. All analyses were performed using both the band gender and singer gender datasets.

1. Musicians' gender over time

Figure 1 shows the band gender and singer gender percentages per category (all-male, all-female, and mixed-gender) over time. When looking at band gender, all-male bands accounted for 65.20% of the sample, all-female bands 19.07%, and mixed-gender bands 15.73%. Linear regression analyses indicated that the presence of all-female bands, $F(1,54)= 46.10$, $p< .001$, $R^2= .451$, and mixed-gender bands, $F(1,54)= 29.9$, $p< .001$, $R^2= .344$, increased significantly over the time span. By contrast, the presence of all-male bands decreased significantly over time, $F(1,54)= 94.80$, $p< .001$, $R^2= .637$.

Results concerning singer gender were very similar. Male singers accounted for 61.63% of the sample, female singers 23.32%, and singers of both genders 15.06%. Linear regression analyses showed that the presence of female singers, $F(1,54)= 76.80$, $p< .001$, $R^2= .579$, and mixed-gender singers, $F(1,54)= 32.3$, $p< .001$, $R^2= .363$, increased significantly over the period, whereas the presence of male singers decreased significantly over time, $F(1,54)= .104$, $p< .001$, $R^2= .653$.

Figure 1. Band gender (top) and singer gender (bottom) percentage over time.



These results provide descriptive information about the proportion of male, female, and mixed-gender musicians across the time span. Nevertheless, we were also interested in identifying critical points in time at which the proportion of musicians' gender changed significantly. Thus, we performed a classification tree model based on permutation tests. The classification tree model was implemented by the R package "party" (Hothorn, Buehlmann, Dudoit, Molinaro, Van der Laan, 2006; Hothorn, Hornik, & Zeileis, 2006; Strobl, Boulesteix, Kneib, Agustin, Zeileis, 2008; Strobl, Malley, & Tutz, 2009). This data mining and machine learning approach allows identification of specific situations in which the distribution of the dependent variable changes significantly, modelling higher-order interaction effects in the predictor variable. Moreover, statistical tree models offer a number of benefits compared to linear regression models in that they can handle large sets of predictor variables and do not assume a linear relationship between predictors and the dependent variable (see Hastie et al., 2009).

We ran separate models with (a) band gender and (b) singer gender as the dependent variables. In the two models, the variable time (at the year level) was the predictor variable (see Figure 2 and Figure 3 for the classification tree structure models). Gender was treated as a categorical variable and had three levels: 0% female (cases were the singer or band was exclusively male), mixed-gender (cases where the singers or band included both female and male members), and 100% female (cases where the singer or band was exclusively female). For each node of the tree, the *p*-values indicate the significance of the split based on the permutation statistics. For each terminal node at the bottom of the graph, bar plots depict the gender distributions of musicians' gender (1= all-male, 2= all-female, and 3= mixed-gender).

Interpretation of the tree models requires starting at the top and following each branch down, to arrive at a terminal node. To arrive at the subset with the highest proportion of male bands (Figure 2, node 4), readers should follow the first "year" node down the "< 1976" branch (left-hand side), descend to the second "year" node down the "< 1968" branch, and then descend to the third "year" node down the "< 1965" branch. In contrast, to arrive at the subsets with the highest proportion of all-female bands (nodes 14 and 15), follow the first "year" node down the "> 1976" branch (right-hand side), descend to the second "year" node down the "> 1984" branch, and then descend to the third "year" node down the "> 2008" year branch. Therefore, each node of the tree identifies conditions that lead to particularly low and high combinations of all-male, all-female, and mixed-gender bands, suggesting different meaningful periods in which band gender changed significantly. The same logic applies to the singer gender model (Figure 3).

In the band gender model, the classification tree revealed seven critical time points between 1960-2015: 1965, 1968, 1976, 1982, 1984, 2008, and 2012. The classification tree of the singer gender model also revealed seven critical years: 1968, 1976, 1980, 1982, 1984, 1996, and 2000.

To further examine whether relevant lyrical themes varied as a function of musicians' gender over time, we organized the variable time into meaningful periods. While previous studies have grouped years into blocks, such as decades or half decades (e.g., Dukes et al., 2003), this approach is problematic because it is arbitrary, likely to lose variance in the data, and overlooks critical periods of change. Thus, we used the outcome of the classification tree models to group the variable time into five periods on each model (Table 2). The five-group solution achieved the best balance in terms of the number of years within each group and it allowed for comparison of both band and singer gender using the same levels. Other possible solutions (a seven-, six-, or four-group solution) would introduce larger imbalance in the number of years within each group, making it more difficult to compare the two datasets directly. Table 3 shows the top five most popular artists in each period and in total, organized by gender category. Popularity was determined by the total number of weeks the artist appeared in the 1-5 positions.

Table 2. Time groups in the band gender and singer gender models.

Group	Band Gender	Singer Gender
1	1960-1968	1960-1968
2	1969-1976	1969-1976
3	1977-1984	1977-1984
4	1985-2008	1985-1996
5	2009-2015	1997-2015

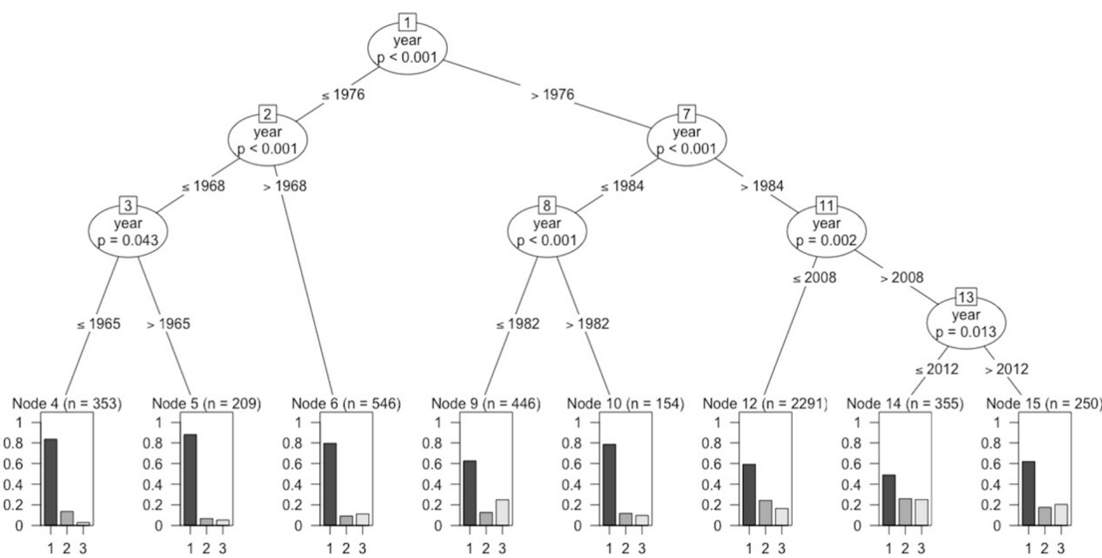
Table 3. Top five most popular artists in each period and in total (with regard to the band gender model). Total number of weeks appears in brackets.

Period	Rank	All-male	All-female	Mixed-gender
1960-1968	*1st*	Beatles (127)	Helen Shapiro (29)	Seekers (28)
(N= 247; *M*= 8.70;	*2nd*	Cliff Richard (97)	Petula Clark (24)	Mamas and Papas (8)
SD= 13.28)	*3rd*	Elvis Presley (90)	Sandie Shaw (19)	Sonny and Cher (8)
	4th	Rolling Stones (45)	Cilla Black (16)	Nancy Sinatra & Frank Sinatra (7)
	5th	Roy Orbison (42)	Shirley Bassey (15)	Esther & Abi Ofarim (6)
1969-1976	*1st*	Slade (52)	Suzi Quatro (11)	New Seekers (32)
(N= 314;	*2nd*	T. Rex (51)	Mary Hopkin (9)	Abba (30)
M= 6.36;	*3rd*	Gary Glitter (37)	Dana (8)	Middle of the Road (16)
SD= 6.59)	*4th*	Sweet (34)	Freda Payne (8)	Peters & Lee (13)
	5th	Bay City Rollers (29)	Diana Ross (7)	Wings (13)
1977-1984	*1st*	Frankie Goes to Hollywood (30)	Donna Summer (22)	Abba (57)
(N= 321; *M*= 6.17;	*2nd*	Shakin' Stevens (30)	Irene Cara (12)	Blondie (34)
SD= 6.83)	*3rd*	Culture Club (29)	Barbra Streisand (10)	Boney M (33)
	4th	Madness (29)	Bonnie Tyler (7)	John Travolta & Olivia Newton-John (21)
	5th	Stevie Wonder (29)	Gloria Gaynor (7)	Bucks Fizz (17)
1985-2008	*1st*	Take That (66)	Madonna (122)	S Club 7 (29)
(N=1,209;	*2nd*	Michael Jackson (48)	Kylie Minogue (59)	Steps (26)
M= 4.93;	*3rd*	Boyzone (46)	Whitney Houston (42)	2 unlimited (24)
SD= 6.66)	*4th*	Westlife (46)	Spice Girls (38)	Ace of Base (18)
	5th	Oasis (38)	Britney Spears (34)	Black Eyed Peas (18)
2009-2015	*1st*	Ed Sheeran (31)	Ellie Goulding (31)	Black Eyed Peas (33)

(N= 409;	2nd	Justin Bieber (29)	Adele (30)	Eminem feat. Rihanna (14)
M= 4.43; *SD*= 5.04)	3rd	Bruno Mars (27)	Lady Gaga (27)	Maroon 5 feat. Christina Aguilera (12)
	4th	Jason Derulo (23)	Taylor Swift (25)	Rihanna feat. Calvin Harris (12)
	5th	AVICII (21)	Rihanna (23)	Gotye feat. Kimbra (11)
TOTAL	1st	Beatles (142)	Madonna (126)	Abba (87)
1960-2015	2nd	Elvis Presley (138)	Kylie Minogue (61)	Black Eyed Peas (51)
(N= 2,287;	3rd	Cliff Richard (137)	Rihanna (53)	Blondie (36)
M= 6.08;	4th	Michael Jackson (74)	Whitney Houston (43)	Boney M (33)
SD= 9.23)	5th	Take That (71)	Spice Girls (38)	New Seekers (32)

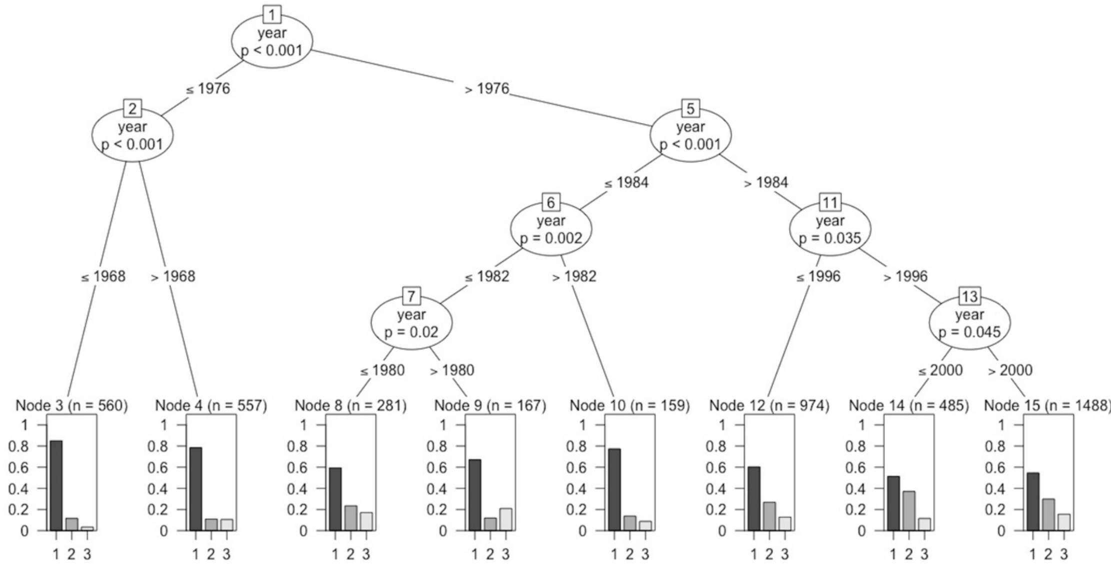
Note. N: Number of artists; M: Mean weeks; SD: Standard deviation. Popularity was determined by the total number of weeks the artist appeared in a 1-5 chart position during the period in question. The artist/group was treated as it appeared on the chart, so that the weekly count does not include additional appearances as a nominated or featured artist in collaboration with other named musicians.

Figure 2. Classification tree model of band gender over time (N= 4,604 observations).



Note. 1= all-male, 2= all-female, 3= mixed-gender bands.

Figure 3. Classification tree model of singer gender over time (N= 4,671 observations).



Note. 1= all-male, 2= all-female, 3= mixed-gender singer(s).

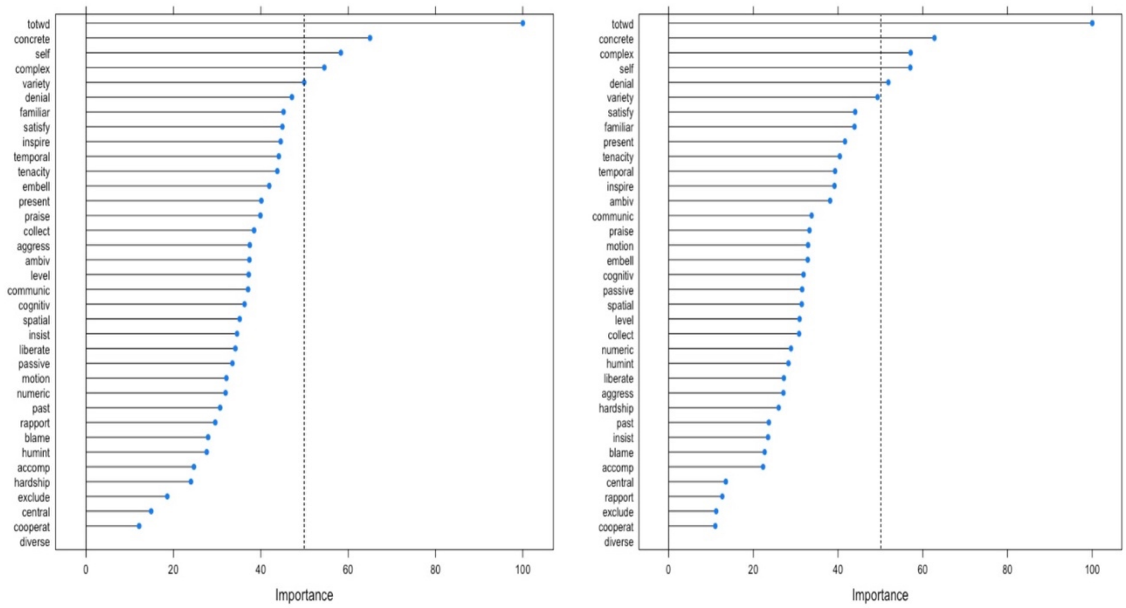
2. Lyrics and musicians' gender: Selecting the most important lyrical themes

To investigate which of the 36 lyrical variables were more strongly associated with musicians' gender, we ran two separate random forest models with band gender and singer gender as dependent variables (a continuous variable indicating the proportion of members or singers who were female). The 36 individual dictionaries were the predictor variables. The random forest algorithm was implemented in R, using the packages *randomForest* (Liaw & Wiener, 2002) and *caret* (Kuhn, 2008), which was also used for tuning of the models and to calculate the R^2 using cross-validation. As with statistical tree models, random forest is a machine learning technique (Breiman, 2001) that can handle complex interactions and large sets of predictor variables, even if they are highly correlated (Hastie et al., 2009; for different applications in music psychology research see Anglada-Tort & Müllensiefen, 2017; Jakubowski, Finkel, Stewart, & Müllensiefen, 2016). Moreover, random forest models use an in-built out-of-the-bag cross-validation mechanism that protects against alpha error inflations and overfitting. The random forest models were run with a size of 10,000 trees. The number of randomly preselected predictor variables to be chosen in each split was six, as determined by a grid search using the R package *caret* (Kuhn, 2008).

To select the best predictive variables associated with changes in musicians' gender, a measure of variable importance score for each predictor (the 36 lyrical variables) was estimated from the data. The variable importance score described how predictive each of the 36 lyrical variables were in comparison to the predictive ability of the other lyrical variables. Thus, a common procedure of feature selection is to rank predictor variables by importance score and select the top performing variables (Breiman, 2001; Kuhn, 2008).

Figure 4 displays the importance scores for each lyrical variable in the band gender (left) and singer gender (right) models. Note that the absolute values of the variable importance scores have no 'real world' meaning: only the difference between variable importance scores should be used for meaningful comparison. For the subsequent analysis, we selected the five best performing variables in the two models, each of which had variable importance scores above 50. Note, however, that one could select further variables, although the strength of their association with the dependent variable would be weaker. Accordingly, *total number of words*, *concreteness*, *self-reference, complexity, and variety* were selected in the band gender model (R^2 = .125); and *total number of words*, *concreteness*, *complexity, self-reference, and denial* were selected in the singer gender model (R^2 =.121).

Figure 4. Variable importance scores for the 36 predictor variables in the random forest model with band gender (left) and singer gender (right).



Note. totwd: total number of words; concrete: concreteness; self: self-reference; complex: complexity; The difference between variable importance scores provides a meaningful comparison; however, the absolute values of the variable importance scores should not be interpreted because they are arbitrary.

3. Lyrics and band gender over time

A series of linear mixed effect analyses, using the R packages "lme4" (Bates, Mächler, Bolker, & Walker, 2015) and "lmerTest" (Kuznetsova, Brockhoff, & Christensen, 2016) investigated the relationship between lyrics and band gender over time. Linear mixed-effects models have several advantages compared to ordinary regression models, as they can handle missing values and non-normal distributions, do not assume independence among observations, and can work with correlated observations. Linear mixed-effects can also model random variability by assuming random intercepts for different relevant factors, such as artist and song titles, providing unbiased estimates of the coefficients of the predictor variables (Baayen, Davidson, & Bates, 2008; Pinheiro & Bates, 2000). Effect sizes were calculated using the R package *MuMIn* (Barton, 2009), which calculates the marginal and conditional coefficient of determination for generalized mixed-effect models. The marginal R^2 of the model (R_m^2) calculates the variance explained by the fixed factors, whereas the conditional R^2 of the model (R_c^2) calculates the variance explained by both fixed and random factors.

Using the band gender dataset, separate analyses were performed for each of the five lyrical variables identified in the random forest procedure as dependent variables: total number of words, concreteness, self-reference, complexity, and variety. See Table 4 for a summary of the five models concerning band gender. In all analyses, the fixed factors were band gender (categorical: all-male, all-female, and mixed-gender), time-group (categorical: 1960-1968, 1969-1976, 1977-1984, 1985-2008, and 2009-2015), and the gender-time interaction, whereas artists and song title were the random effect factors. Here, we report in detail the total number of words and self-reference models for which the interaction term was significant. See Appendix A for the top five artists by gender in each period and in total concerning the number of total words per song and use of self-reference; and Appendix B for graphical figures with the models in which the interaction term was nonsignificant.

Table 4. Summary table of the linear mixed-effects models with band gender

	Sum of Sq	*df*	*F*	*p*-value	R_m^2	R_c^2
*1. Total words**					.081	.989
Time	75818	4	57.84	< .001		
Band Gender	618	2	.94	.39		
Interaction	11822	8	4.51	< .001		
2. Concreteness					.018	.967
Time	111.972	4	2.74	.03		
Band Gender	31.89	2	1.56	.21		
Interaction	120.58	8	1.47	.16		
*3. Self-reference**					.015	.977
Time	270.64	4	4.22	.002		
Band Gender	305.41	2	9.54	< .001		
Interaction	404.11	8	3.15	.001		
4. Complexity					.018	.967
Time	.14	4	9.40	< .001		
Band Gender	.02	2	2.22	.11		
Interaction	.06	8	1.95	.05		
5. Variety					.06	.969
Time	.04	4	23.49	< .001		
Band Gender	.002	2	2.04	.13		
Interaction	.006	8	1.87	.06		

Note. R_m^2*: marginal* R^2 *of the model;* R_c^2*: conditional* R^2 *of the model. The asterisks (*) indicate the models in which the interaction term is significant and, therefore, reported in detail in text.*

The linear mixed effect model concerning total number of words as dependent variable (Figure 5) revealed a significant main effect of time ($p < .001$), nonsignificant main effect of gender ($p= .39$), and a significant gender-time interaction ($p < .001$). The R_m^2 (variance explained by the fixed factors alone) was .081 and the R_c^2 (variance explained by both fixed and random effect factors) was .989. The linear mixed effect model regarding self-reference (Figure 6) showed significant main effects of time ($p= .002$), band gender ($p< .001$), and a significant gender-time interaction ($p= .001$). The R_m^2 and R_c^2 were .015 and .977, respectively.

Figure 5. Total number of words and band gender over time

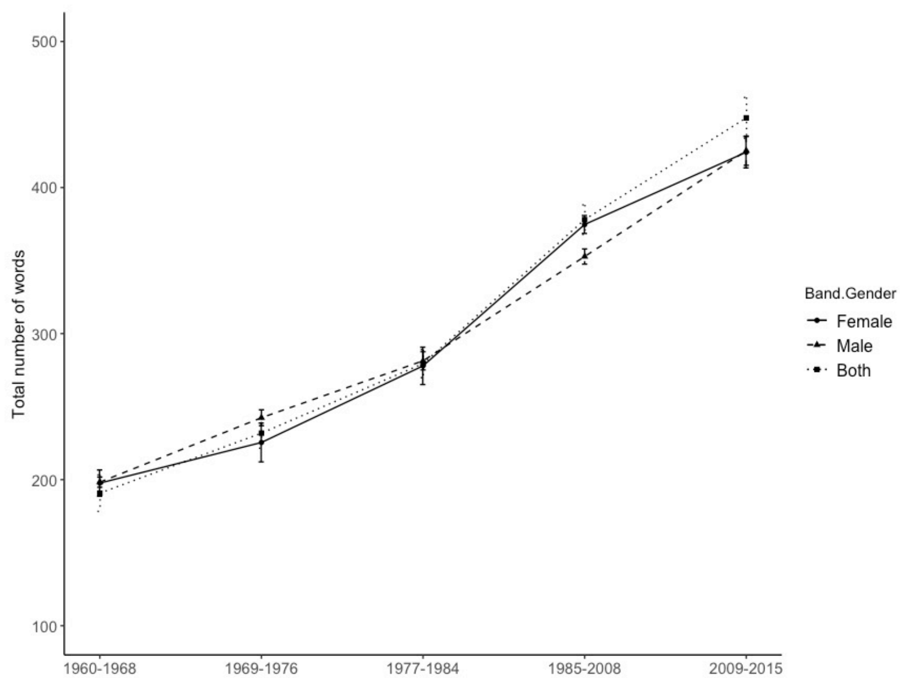
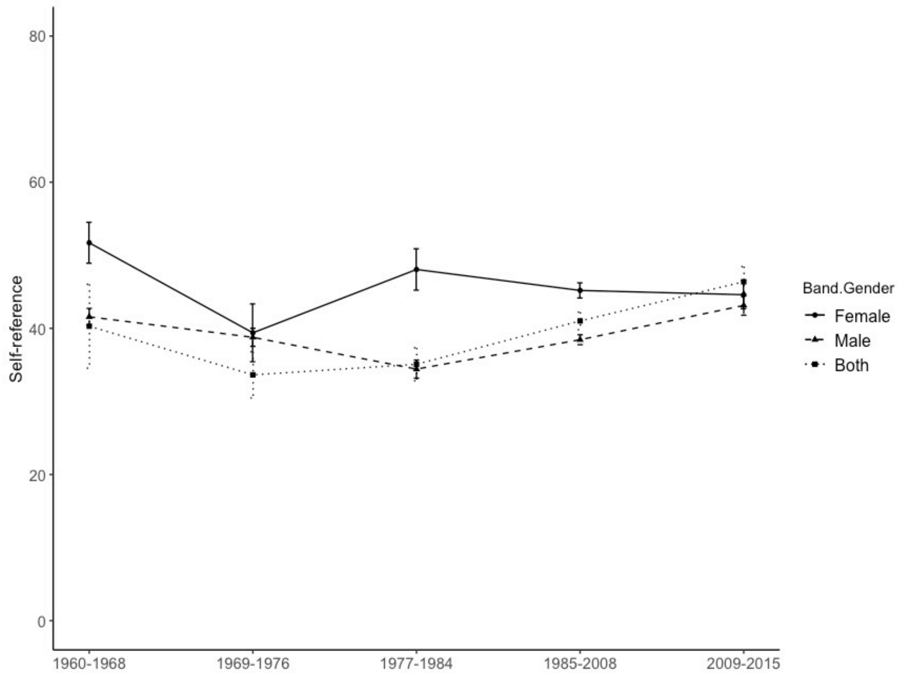


Figure 6. Self-reference (i.e., all first-person references) and band gender over time



4. Lyrics and singer gender over time

Using the same analysis protocol, analyses were performed concerning singer gender employing the total number of words, concreteness, complexity, self-reference, and denial as dependent variables. See Table 5 for a summary of the five models concerning singer gender. The fixed factors were singer gender (categorical: male, female, and mixed-gender), time-group (categorical: 1960-1968, 1969-1976, 1977-1984, 1985-1996, and 1997-2015), and the gender-time interaction, whereas artists and song title were the random effect factors. The reported findings below concern the total number of words model in which the interaction term was significant. See Appendix C for graphical figures with the models in which the interaction term was nonsignificant.

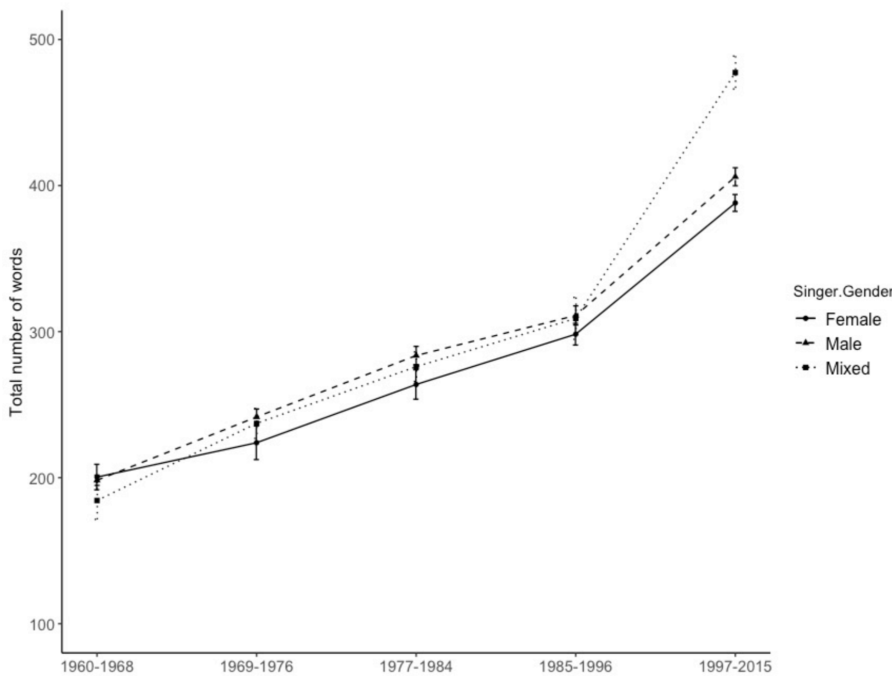
Table 5. Summary table of the linear mixed-effects models with singer gender

	Sum of Sq	*df*	*F*	*p*-value	R_m^2	R_c^2
*1. Total words**					.099	.983
Time	144809	4	76.92	< .001		
Singer Gender	7305	2	7.76	< .001		
Interaction	8080	8	2.15	.03		
2. Concreteness					.006	.959
Time	155.4	4	4.11	.003		
Singer Gender	.23.5	2	1.24	.29		
Interaction	29.5	8	.39	.93		
3. Complexity					.015	.967
Time	.16	4	11.28	<.001		
Singer Gender	.01	2	1.70	.18		
Interaction	.04	8	1.39	.19		
4. Self-reference					.016	.978
Time	304.89	4	4.98	< .001		
Singer Gender	358.71	2	11.73	<. 001		
Interaction	222.40	8	1.82	.07		
5. Denial					.004	.998
Time	4.31	4	1.96	.10		
Singer Gender	1.68	2	1.52	.22		
Interaction	6.61	8	1.50	.15		

Note. R_m^2: marginal R^2 of the model; R_c^2: conditional R^2 of the model. The asterisks (*) indicate the models in which the interaction term is significant and, therefore, reported in detail in the text.

The linear mixed effect model with total number of words as dependent variable (Figure 7) revealed significant main effects of time ($p < .001$), singer gender ($p < .001$), and the gender-time interaction ($p = .03$). The R_m^2 and R_c^2 were .099 and .977, respectively.

Figure 7. Total number of words and singer gender over time



Discussion

The present study investigated how the gender representation of the UK's most popular musicians has changed over time and the extent to which these changes might relate to popular song lyrics. As predicted, there was a significant inequality in gender representation. Overall, all-male bands and singers accounted for more than 60% of the data. The gender gap also becomes apparent when looking at the top 10 most popular artists in our dataset (determined by the total number of weeks the artist charted in the 1-5 top positions): eight of the ten artists were male, with the Beatles ranking highest (with 142 weeks), followed by Elvis Presley (138 weeks), and Cliff Richard (137 weeks). Madonna, in the fourth position (126 weeks), was the only female artist in the top 10 and Abba, in the fifth position (87 weeks), the only mixed-gender artist.

We also found evidence supporting the hypothesis that the prevalence of female musicians in the single sales charts has increased significantly over time. This was true for both all-female bands and singers (Figure 1), who went from a prevalence of 11.64% (all-female bands) and 12.08% (female singers) in the 1960s to a prevalence of 23.82% and 29.75% between 2006-2015, respectively. By contrast, the presence of all-male bands and male singers decreased significantly: from an initial prevalence of 84.35% (male bands) and 83.92% (male singers) to 54.95% and 49.97% in 2006-2015, respectively. These findings concerning the UK's singles sales charts are consistent with previous American research on the role of female artists in popular music (Dukes et al., 2003; Hesbacher et al., 1977; Lafrance, et al., 2011; Wells, 1986, 1991, 2001).

Seven critical inflection points were identified at which the prevalence of all-female bands and singers changed considerably (Figure 2 and 3). In both band and singer gender models, the most relevant points of change were in the years 1968, 1976, and 1984. For instance, in 1977, all-male bands decreased from 75% (in 1976) to 65% (in 1977), but all-female bands increased from 11% (in 1976) to 18% (in 1977). Similarly, in 1985, all-female bands increased from 16% (in 1984) to 30% (in 1985) and all-male bands decreased from 77% (in 1984) to 61% (in 1985). Thus, the classification tree model indicated 1977 and 1984 as critical years of change. Note that the increase in the prevalence of female artists was highest in the 1985-2008 period. For example, the top 5 most popular female artists during 1985-2008 were Madonna (122 weeks), Kylie Minogue (59 weeks), Whitney Houston (42 weeks), the Spice Girls (38 weeks), and Britney Spears (34 weeks; see Table 3). Interestingly, Wells (1991) also identified a peak year for female artists in the UK in 1985 and found that the prominence of female artists in the US increased notably around 1985, 1996, and 1999 (Wells, 1991, 2001).

It is of course tempting to note that the inflection points highlighted coincide with some significant moments in UK culture. These include the surge in popularity of the women's rights movements (1968), the rise of punk (1976), the peak in popularity of Margaret Thatcher's prime ministership (1984), and, more generally, third wave feminism (1990-2012). Thus, these findings open up intriguing questions, namely, what particular factors contributed to the observed increase in female and mixed-gender artist in the UK and the global music market; and why did the critical years identified in this study lead to drastic changes on the prevalence of female and male artists in the singles sales charts? Future work may wish to address these questions, considering the extent to which this can be attributed to the quality of the music, societal factors, and music industry marketing.

The second research aim was to explore whether (and how) UK popular music lyrics might have changed over time as a function of musician gender. Random forest analyses allowed us to select the most important lyrical themes associated with the proportion of musicians' gender (Table 1). The results were very similar in both the band and singer gender models, identifying the total number of words, concreteness, self-reference, and complexity as the most important. Indeed, the total number of words was almost twice as important as the next-ranked variable (i.e., concreteness) in predicting musicians' gender in the two models. Nevertheless, it is worth noting that the 36 lyrical variables explained only 10% of the variance in the outcome variable (i.e., the prevalence of band or singer members who were female). This suggests that the associations between the lyrical content of popular music and the artists' gender, although existent, are rather small in size.

In the band gender analyses, two models resulted in significant gender-time interactions (i.e., total number of words and self-reference), whereas in the singer gender analyses, only one model gave rise to a significant interaction term (i.e., total number of words). When looking at the gender of the band, the analysis considering the total number of words showed that from 1960 to 2015, there was a significant increase in the total number of words used by musicians (Figure 5). This increase was large in size, with an average of fewer than 200 words per song in the 1960s to an average of more than 400 words per song from 2006-2015. Overall, all-male bands, all-female bands, and mixed-gender bands did not differ significantly in the total number of words they used. However, the interaction between time and gender indicated that the total number of words used in songs by the three band gender categories differed significantly depending on the period. In 1969-1976, all-male bands used more words in their songs (average of 242.40 words per song) than did all-female (average of 225.46 words per song) and mixed-gender bands (average of 231.83 words per song). But in 1985-2008 all-female (average of 274.70 words per song) and mixed-gender bands (average of 379.02 words per song) used more words in their lyrics than all-male bands (average of 352.76 words per song). The model concerning singer gender led to similar results, but there were some notable differences (Figure 6). For example, from 1960-1968 female and male singers used approximately the same number of words in their lyrics, but in the following four periods (spanning 1969 to 2015) male and mixed-gender singers used more words in their lyrics than did female singers. In addition, the total number of words used in songs by mixed-gender singers increased drastically in the last period (1997-2015) compared to the other two gender groups.

It is plausible that one of the most relevant factors contributing to the increase in the use of words per song over time is the rise of rap music in UK and US (see Dukes et al., 2013; and Smith, 2014). In fact, those bands and singers that use the highest number of words per song are predominantly hip hop and rap artists (see Appendix A, which shows, for example, that the So Solid Crew had the greatest number of words, averaging 1112.5 words per song, followed by Nelly, with an average of 1095 words). The interaction between gender and time is, however, more difficult to interpret. One possibility is that this could be, at least partly, due to three different phases in the rise of rap and hip hop involving a first phase of predominantly male rappers, followed by an increase of female rappers, and, finally, a rise of collaborative rap performances leading to an increase of mixed-gender bands and singers (The Economist, 2018).

Regardless of gender, it is interesting to note that this general increase in the total number of words over time contrasts with the significant decrease observed in variety (i.e., the number of different words divided by the total words) and complexity (i.e., mean number of characters per word) (see Table 4 and appendix B). Note that these two lyrical variables measure diversity of vocabulary. Thus, UK popular music lyrics have become longer, but simpler and more repetitive over time. This finding mirrors Morris' study

(2017; https://pudding.cool/2017/05/song-repetition/), which analysed the repetitiveness of a dataset of 15,000 songs that charted on the Billboard Hot 100 between 1958 and 2017.

The other significant time-gender interaction in the band gender model concerned self-reference. Overall, all-female bands used significantly more self-reference in their lyrics (*M*=45.47) than all-male bands (*M*= 40.37) and mixed-gender bands (*M*=38.97). However, the significant time-gender interaction revealed that this difference was particularly large in the periods 1960-1968 and 1977-1984 (Figure 6). For example, in 1960-1968, all-female bands had a mean self-reference score of 51.71, whereas all-male and mixed-gender bands averaged 41.58 and 40.29, respectively. In this period, the female artists with highest use of self-reference were Millie Small (with the song "My Boy Lollipop") and Nina Simone (with the song "Ain't got no/ I got life)". Nevertheless, in the 1969-1976 period, the use of self-reference in songs by all-female bands (*M*= 39.38) decreased almost to the levels of all-male bands (*M*= 38.77); and in the latest period studied (2009-2015), self-reference decreased (*M*= 44.60) again almost to the levels of all-male bands (*M*= 43.13) and below the levels of mixed-gender bands (*M*= 46.37). The decrease in the use of self-reference by female artists starting in 1968 and 2008 relate to two critical points in the history of feminism, namely, the surge in popularity of the women's right movement in 1968 and third wave feminism from 1990 to 2012. Arguably, the increasing awareness of this collective movement in 1968 and the 1990s could explain female artists' decreasing use of first-person references. Future research could explore this further by looking at the prevalence of the gender of composers, songwriters, and producers of popular music over time.

The research presented here has several limitations. First, by analysing the lyrics of those songs that reached the top 5 in the UK single sales charts, our results cannot be generalised to music charting in other positions or in other countries. Second, the classification of musicians' gender was based on biographical sources (e.g., music industry web sites and music encyclopaedias). We had no data on the actual gender with which the artists identified themselves (nor *the extent* to which they identified with a particular gender). Third, we were not able to identify the specific contribution of each individual musician to the final composition (including the production of the lyrics) and recording. Further, we were unable to consider the role of other parties in this process, such as songwriters, managers, producers, and other music industry professionals. In this context, it is notable that female songwriters and producers are also underrepresented in the music industry, representing only 12% of songwriters and 2% of producers (Smith, Choueiti, & Pieper, 2018).

In summary, the present results show that the UK's most popular music from 1960 to 2015 is characterized by a large gender inequality. This finding is similar to that found previously in the US music market, which is particularly regrettable since the US and UK represent two of the most powerful music industries in the world. The fact that female artists are still unrepresented in the single sales charts in the 2010s is concerning, and merits further investigation. However, we found that the presence of female and mixed-gender artists increased significantly over the time span considered. We were also able to identify the most important years leading to significant increases in the prevalence of female and mixed-gender artists, namely, 1968, 1976, and 1984. Additionally, our results indicated that the total number of words per song was the most important lyrical variable associated with changes in musicians' gender. Nevertheless, the 36 lyrical themes examined only explained 10% of the variance in the proportion of musicians who were female, suggesting only a weak association between lyrical content and musicians' gender. Despite this, we found interesting patterns of change over time in the use of specific lyrical variables (i.e., total number of words and self-reference) between male, female, and mixed-gender bands and artists. Moreover, our findings suggest that UK's popular music lyrics became more repetitive over time: while the total number of words increased significantly over time, the diversity of vocabulary employed decreased.

Finally, the computational approach used in the current study presents important methodological improvements over previous research. The majority of previous studies employed small datasets, a limited range of lyrical variables, and human coders to analyse the lyrical content of the songs. By contrast, the approach used in this study allowed for a computerised analysis of 36 discrete lyrical themes on a total of 4,222 songs performed by 2,287 artists, covering 55 years (1960-2015). The use of data mining and machine learning techniques (e.g., classification tree models and random forest) offered several advantages in comparison to the statistical tools (e.g., chi-squared tests, ANOVAs, and linear regression models) used in earlier studies. The potential applications of machine learning and data mining techniques are particularly useful when working with large datasets with many variables, even when there are non-linear and complex relationships between dependent and predictor variables, and the predictor variables are highly correlated (Hastie et al., 2009). Note that these characteristics may well be common when considering data derived from the music industry, including naturalistic singles sales charts data. Thus, these techniques will be valuable for future music psychology research.

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Appendix A

Top five bands on each period and in total with the highest number of total words per song, organized by gender

Period	Rank	All-male	All-female	Mixed-gender
1960-1968	*1st*	Wink Martindale (577)	Mary Hopkins (367)	Peter Sellers & Sophia Loren (365)
(N= 247; *M*= 198.36; *SD*= 69.14)	*2nd*	Bob Dylan (411)	Mary Wells (2818)	Honeycombs (258)
	3rd	Val Donnican (406)	Helen Shapiro (*M*= 261.5; *SD*= 37.72)	Ike & Tina Turner (245)
	4th	Napoleon XIV (385)	Diana Ross & the Supremes (257)	Steve and Eydie (236)
	5th	Tommy Steele (380)	Twinkle (251)	Julie Driscoll, Brian Auger, & the Trinity (224)
1969-1976	*1st*	Don McClean (889)	Suzi Quatro (*M*= 377.34; *SD*= 254.28)	Elgins (359)
(N= 314; *M*= 237.78; *SD*= 99.81)	*2nd*	The Goodies (715)	Sylvia (337)	Blue Mink (*M*= 346.67; *SD*= 78.52)
	3rd	Laurie Lingo & the Dipsticks (694)	Carly Simon (318)	R & J Stone (322)
	4th	C.W. McCall (670)	Diana Ross & the Supremes & the Temptations (309)	Brotherhood of Man (306)
	5th	Benny Hill (637)	Diana Ross (*M*= 301; *SD*= 141.42)	Candi Staton (306)
1977-1984	*1st*	Sovine (738)	Chaka Khan (571)	Motorhead & girlschool (555)
(N= 321; *M*= 285.69; *SD*= 108.74)	*2nd*	Sugarhill Gang 661)	Donna Summer & Barbara Streisand (508)	Fun Boy Three & Bananarama (527)
	3rd	Keith Mitchell (655)	Laura Branigan (495)	Shaky & Bonnie (438)
	4th	Detroit Spinnners (621)	Suzi Quatro (447)	Style Council (427)
	5th	Tony Capstick & the Carlton Main Frickley Colliery Band (621)	Gloria Gaynor (446)	Fiddler's Dram (421)
1985-2008	*1st*	Nelly (*M*= 1095; *SD*= 527.50)	Kelly Rowland feat. Eve (771)	So Solid Crew (*M*= 1112.5; *SD*= 147.78)

(N= 1,209;	*2nd*	Nelly Feat. City Spud (1066)	Lisa Maffia (700)	Busta Rhymes & Mariah Carey feat. The Flipmode Squad (892)
M= 360.47; *SD*= 175.07)	*3rd*	Chamillionaire feat. Krayzie Bone (1053)	Gwen Stefani feat. Eve (682)	Deacon Blue (886)
	4th	Eminem (*M*= 959.07; *SD*= 223.48)	Amerie (617)	Beyonce feat. Slim Thug (852)
	5th	Queen with Wyclef Je (949)	Eve feat. Gwen Stefani (608)	Wyclef Jean feat. The rock & Melky Sedeck (850)
2009-2015	*1st*	Eminem (*M*= 1045; *SD*= 401.90))	Willow (777)	Will.i.am/ Cyrus/ Khalifa (928)
(N= 409;	*2nd*	Justin Timberlake (1040)	Pink (648)	Wiley feat Ms. D (822)
M= 430.03; *SD*= 166.75)	*3rd*	Eminem feat. Dr Dre & 50 Cent (935)	Jessie J / Grande/ Minaj (631)	Tinie Tempah feat. Jess Glynne (804)
	4th	T.I. Feat. Justin Timberlake (897)	Iggy Azalea feat. Rita Ora (627)	Roll Deep (*M*= 801; *SD*= 1.41)
	5th	Jeremih Feat. YG (839)	Katy B feat Ms Dynamite (620)	Eminem feat. Rihanna (793)
TOTAL (1960-2015)	*1st*	Nelly (*M*= 1095; *SD*= 527.50)	Willow (777)	So Solid Crew (*M*= 1112.5; *SD*= 147.78)
(N= 2,287;	*2nd*	Nelly Feat. City Spud (1066)	Kelly Rowland feat. Eve (771)	Will.i.am/ Cyrus/ Khalifa (928)
M= 334.43; *SD*= 167.44)	*3rd*	Chamillionaire feat. Krayzie Bone (1053)	Lisa Maffia (700)	Busta Rhymes & Mariah Carey feat. The Flipmode Squad (892)
	4th	Eminem (*M*= 978.17; *SD*= 260.86)	Gwen Stefani feat. Eve (682)	Deacon Blue (886)
	5th	Queen with Wyclef Je (949)	Jessie J / Grande/ Minaj (631)	Beyoncé feat. Slim Thug (852)

Note. N: Number of artists; M: Mean; SD: Standard deviation. M and SD are only provided in those cases where there is more than one song per artist. The artist/group was treated as it appeared on the chart, so that the weekly count does not include additional appearances as a nominated or featured artist in collaboration with other named musicians.

Top five bands on each period and in total with the highest scores in self-reference (i.e., use of all first-person references in the lyrics), organized by gender

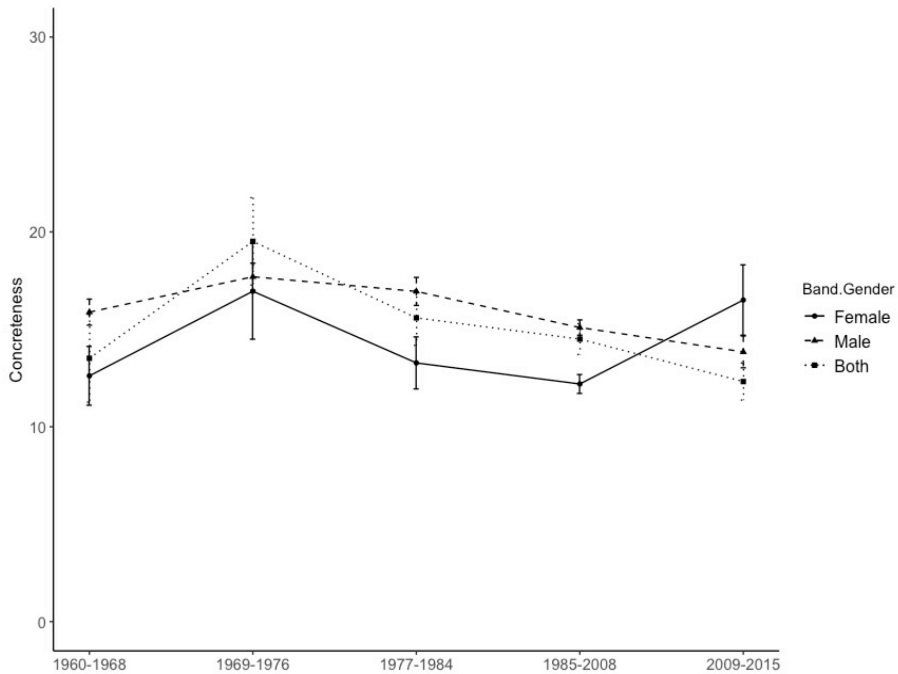
Period	Rank	All-male	all-female	Mixed-gender
1960-1968	*1st*	Clarence 'Frogman' Henry (114.38)	Millie (109.38)	Honeycombs (71.23)
(N= 247;	*2nd*	Overlanders (107.14)	Nina Simone (86.96)	Esther and Abi Ofarim (68.97)
M= 41.36; *SD*= 22.48)	*3rd*	Bonzo Dog Doo-Dah Band (88.82)	Ronettes (77.52)	Sonny & Cher (64.87)
	4th	Barry Ryan (85.32)	Julie Rogers (71.59)	Ike & Tina Turner (59.18)
	5th	P J Proby (82.78)	Susan Maughan (70.55)	Springfields (50.63)
1969-1976	*1st*	Tremeloes (*M*= 111.94; *SD*= 33.52)	Lyndsey de Paul (124.05)	Peter, Paul & Mary (85.03)
(N= 314;	*2nd*	David Dundas (110.55)	Diana Ross & the Supremes & the Temptations (87.38)	Elton John And Kiki Dee (79.86)
M= 37.94; *SD*= 23.77)	*3rd*	Joe Dolan (109.51)	Donna Summer (80.25)	Bobbie Gentry & Glen Campbell (78.61)
	4th	Fleetwood Mac (*M*= 93.345; *SD*= .09)	Clodagh Rodgers (*M*= 69.65; *SD*= 41.24)	Mac & Katie Kissoon (64.93)
	5th	Ken Boothe (91.58)	Dorothy Moore (68.38)	Pickettywitch (54.88)
1977-1984	*1st*	Dee D Jackson (133.56)	Chaka Khan (94.82)	Dollar (*M*= 88.23; *SD*= 18.45)
(N= 321;	*2nd*	Beatles (97.35)	Anita Ward (81.56)	Kid's From Fame (71.43)
M= 36.26; *SD*= 23.06)	*3rd*	Vapors (92.01)	Lene Lovich (80.39)	Bardo (68.46)
	4th	Slade (89.37)	Stephanie Mills (79.82)	Boystown Gang (67.89)
	5th	Mr Big (89.36)	Gloria Gaynor (72.87)	Darts (*M*= 65.45; *SD*= 45.23)
1985-2008	*1st*	Eric Prydz (151.52)	Spagna (100.42)	The Cardigans (126.56)
(N= 1,209;	*2nd*	Benny Benassi presents the Biz (145.46)	Judy Boucher (99.3)	Evanescece feat. Paul McCoy (97.01)
M= 39.86; *SD*= 23.48)	*3rd*	Camisra (125)	Temptations (98.16)	Ting Tings (96.63)
	4th	Adam Rickitt (103.12)	Sybil (93.56)	Livin' joy (95.05)
	5th	Brother Beyond (100.38)	Charlotte Church (90.90)	Jay-Z feat Beyonce Knowles (92.96)
2009-2015	*1st*	Galantis (193.01)	Agnes (107.27)	Rudimental feat. Ella Eyre (121.62)
(N= 409;	*2nd*	Usher feat. Will.I.Am (105.85)	Willow (95.43)	Chase & Status Feat. Moko (107.39)

M= 44.20; *SD*= 23.74)	*3rd*	Secondcity (93.46)	Icona Pop feat. Charli XCX (91.46)	Dr. Kucho/ Gregor Salto/ Ane Brun (95.02)
	4th	David Zowie(89.96)	Cheryl (*M*= 77.83; *SD*= 26.15)	Cash Cash feat. Bebe Rexha (87.56)
	5th	Tinchy Stryder feat. Taio Cruz (89.88)	Demi Lovato (77.1)	Clean Bandit (87)
TOTAL (1960-2015)	*1st*	Galantis (193.01)	Dee d Jackson (133.56)	The Cardigans (126.56)
(N= 2,287;	*2nd*	Eric Prydz (151.51)	Lyndsey de Paul (124.05)	Rudimental feat. Ella Eyre (121.62)
M= 40.22; *SD*= 23.34)	*3rd*	Benny Benassi presents the Biz (145.46)	Millie (109.38)	Chase & Status Feat. Moko (107.39)
	4th	Camisra (125)	Agnes (107.27)	Route 94 feat. Jess Glynne (101.69)
	5th	Clarence 'Frogman' Henry (114.38)	Spagna (100.42)	Evanescece feat. Paul McCoy (97.01)

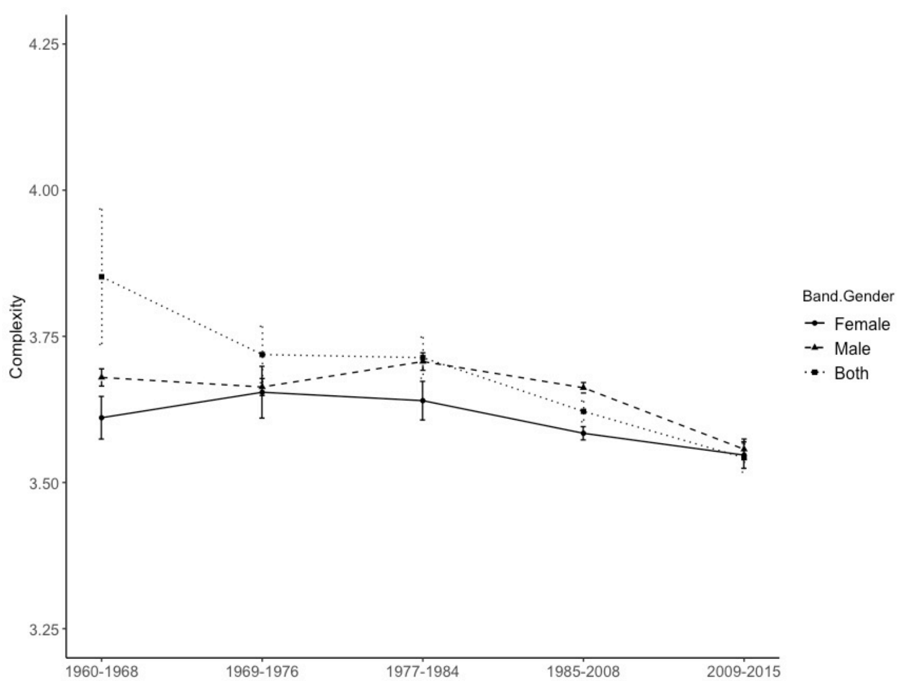
Note. N: Number of artists; M: Mean; SD: Standard deviation. M and SD are only provided in those cases where there is more than one song per artist. The artist/group was treated as it appeared on the chart, so that the weekly count does not include additional appearances as a nominated or featured artist in collaboration with other named musicians.

Appendix B

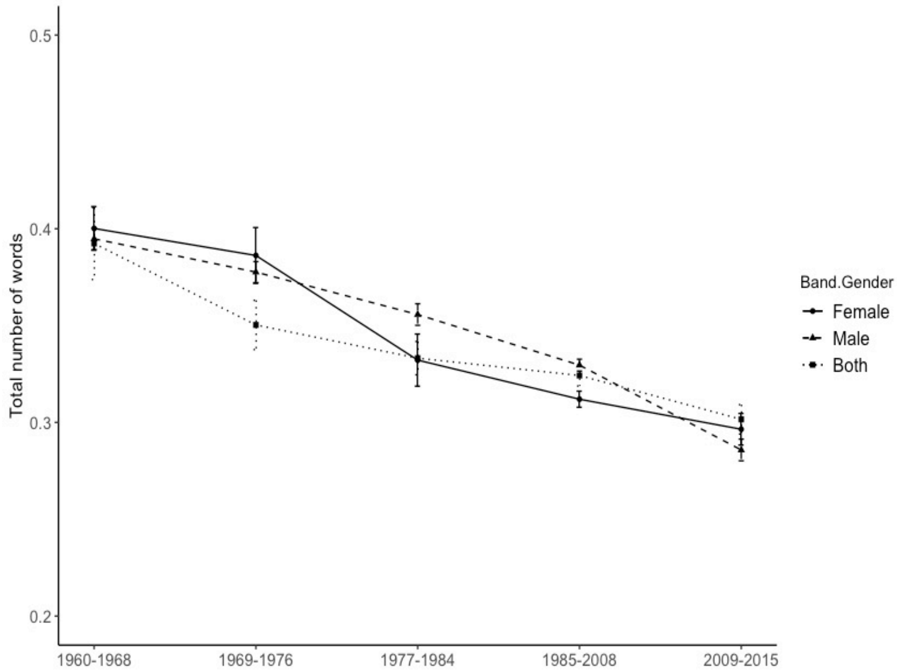
Concreteness (i.e., words concerning tangibility and materiality) and band gender over time



Complexity (i.e., mean number of characters per word) and band gender over time

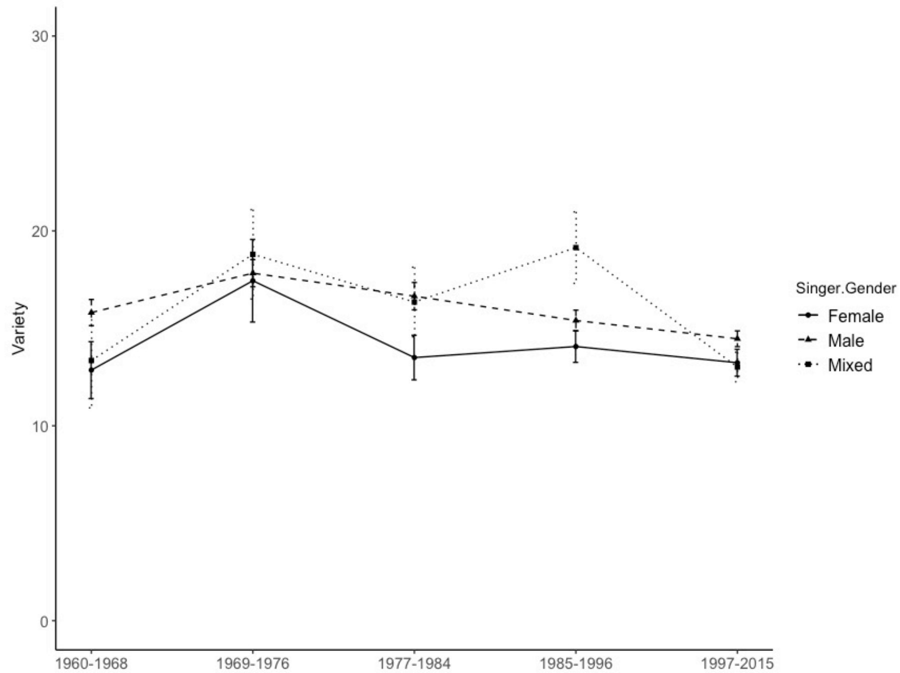


Variety (i.e., the number of different words divided by total words.) and band gender over time

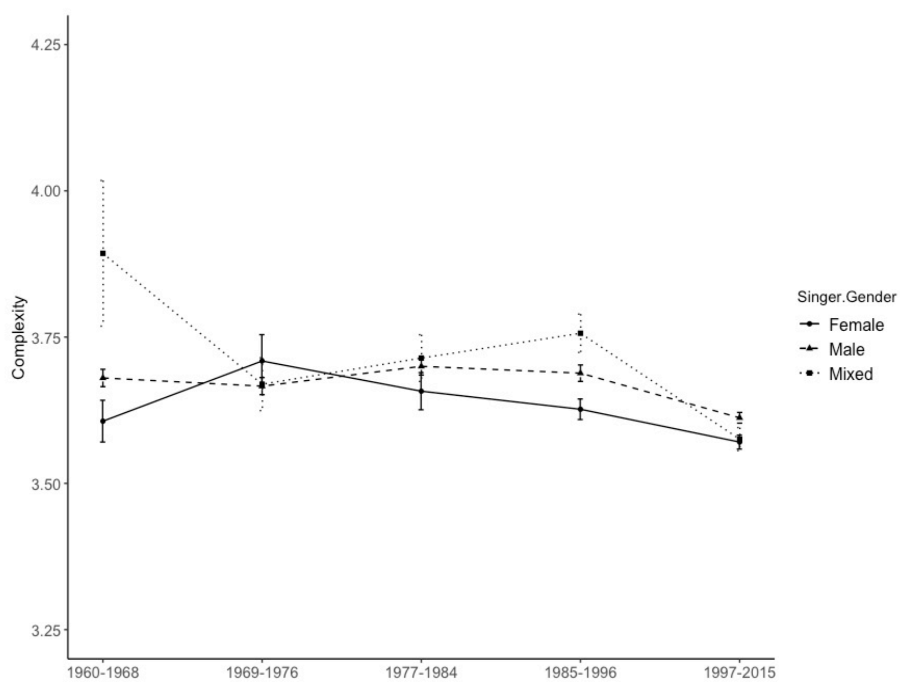


Appendix C

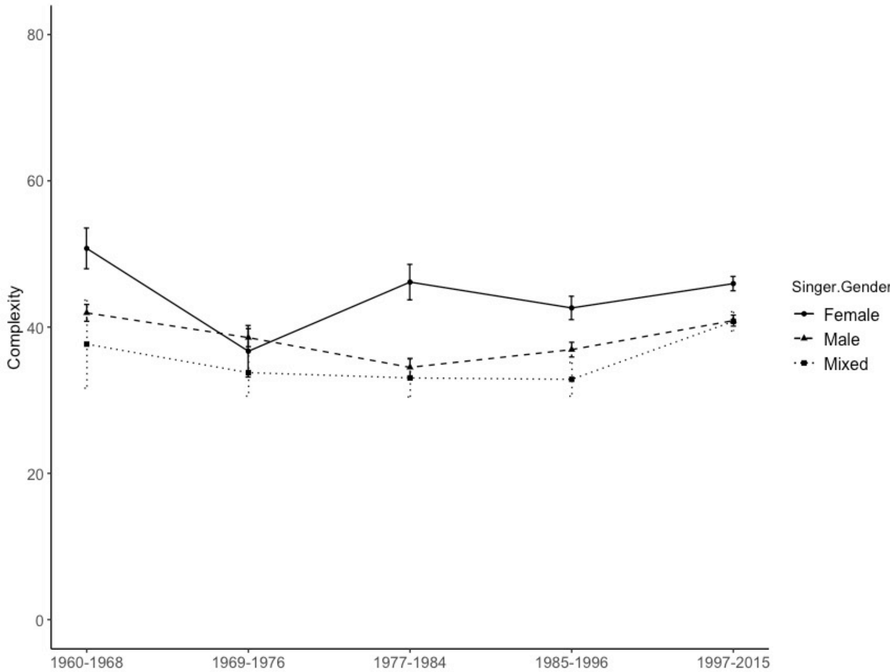
Concreteness (i.e., words concerning tangibility and materiality) and singer gender over time



Complexity (i.e., mean number of characters per word) and singer gender over time



Self-reference (i.e., all first-person references) and singer gender over time



Denial (i.e., negative contractions and negative function words) and singer gender over time