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Evolution over 62 years: an analysis of sexism in the lyrics of the most-listened-to songs in Spain

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ABSTRACT

Sexism against women remains an entrenched problem, manifested in contemporary cultural production worldwide. Since cultural production can be understood as both a mirror for and a reflection of the society where it is inserted, the persistence of sexism in music might rather represent how sexist our society is. The present work aims to analyze the evolution of sexism towards women among the most listened to music lyrics during the past six decades in Spain. To perform a large-scale analysis, automatic text classification based on manually labeled training data is used to categorize music lyrics as sexist or non-sexist. The findings show that sexism has always been present in song lyrics in Spain, and the presence of it has increased considerably in the music made available through streaming platforms over the last decade. This research has the potential to help detect, monitor, and mitigate sexist biases, while also advancing the automation of some aspects of content analysis within the realm of cultural studies.

Introduction

Within contemporary cultural production, music has been argued to be the most consumed product (Bennett, 2001), in particular due to the high spread of music video clips (Illescas, 2015). From a feminist perspective, music narratives and aesthetics have received special attention (Guarinos & Sedeño-Valdellos, 2020; Guarinos, 2012), and women's role has been largely problematized mostly within popular music genres such as rap and lately, reggaeton (e.g. Araüna et al., 2020; Armstrong, 2001; Griffin & Fournet, 2020).

Music production can be considered as an archive of social interpretations within the culture it is inserted in Whiteley, (1992). Indeed, the different currents of post-modernity believe that 'culture is reality' (Kotarba, 1994). Music production, in this sense, sets its lyrics as archives where language can be explored among the axes of power and how such reality has been constructed (Bryant, 1982; Richardson, 1991; Van Maanen, 1995).

Both postmodern and feminist perspectives argue that music and lyrics are elements that embody a state or condition (Swidler, 1996), that may help to build a stronger self (Van Bohemen et al., 2018) or to continue perpetuating gender roles and stereotypes (Álvarez-Cueva et al., 2021). Moreover, when considering text and music, violent metaphors should not be deemed as simple figures of speech (Eisikovits & Buchbinder, 1997). Verbal acts can go beyond melodies up to discriminate and mislead rights, values and traditions of individuals or a group of people. In this sense, lyrics may create an everyday reality available for everyone, which is especially relevant when considering its potential to influence people's behavior (Walker, 1994), driven by its impact on emotions (Eze, 2020).

Some studies have argued that listening to altruistic and caring lyrics increases the interpersonal empathy and helps to improve behavior, well-being and pro-social thought (Álvarez-Cueva, 2022), while others have shown that listening to aggressive lyrics can strengthen violent thoughts, hostile sentiments

(Anderson et al., 2003), and perpetuate discrimination and sexism, specially towards women and LGBTQ+ groups (Dhoest et al., 2015). Hence, it is a matter of concern that ideas behind lyrics might be discriminatory. Indeed, the debate among scholars on what lyrics tell about our society and reality is still open.

Previous studies, often focused on the most listened songs, have pointed out the existence of gender and racial bias in music lyrics. Such studies have ranged from the analysis of stereotypical portrayals of women e.g. Kipsigis secular songs (Koskei et al., 2018), to the analysis of gender roles, stereotypes, and objectification (Oyeka, 2019; Rasmussen & Densley, 2017, Smiler et al., 2017a). In so doing, a number of findings seemed to continue to overlap in relation to sexism and sexual portrayals, especially followed by feminist scholars' debates towards self-determination, new ways of sexualization, and the continued objectification of feminine[1] bodies (Gill, 2017).

Moreover, most of the techniques used to perform these investigations involve content analysis, usually using manual coding (further problematized by a critical perspective and qualitative approaches). In so doing, researchers generally struggle to use large samples of data when analyzing representations in music production – either among images or lyrics (Domènech, 2018).

The main goals of the present study are (1) to examine sexism against women in a large music data collection, by (2) developing a high-accuracy automatic labeling process to detect such sexism, using manually labeled data to 'train' a machine learning scheme. In so doing, this study is focused on the most listened to songs in Spain in last six decades, with a sample of more than two thousand songs.

The organization of this article includes a theoretical section (§II), related work (§III), a description of materials and methods (§IV), results (§V), conclusions (§VI) and limitations (§VII).

Theoretical framework on sexism in music

Within post-modernity (Hall, 2011), sexualization of western culture – the fascination with sex in pseudo new ways, argues how sexual portrayals and the striptease culture have permeated the cultural production to the point of saturation (Attwood, 2009). In this context, current sexual representations may challenge historical portrayals (e.g. objectification of women's body) by subverting the sexualization of the self (self-sexualization) (Gill, 2003, 2017). However, it may also overlap with previous patters of oppression and stigmatization, especially in relation to women and gender roles. Among these contradictions that tend to obscure the levels of differences and their implication on individuals and processes of identification (Skeggs, 1997), sexism is still a major unresolved issue in cultural production.

Sexism is understood as the preconception (based on sex differences) against women – and anything feminine related, with the belief that heterosexual men are superior in terms of ability and intelligence, among others, and thus that women – and by extension anything feminine, deserve less treatment or benefit (U.N.O.D.C., 2018). Scholars and media debates on sexism (e.g. in television, radio, and social networks) aligned with the concern towards it– as a discrimination practice that historically implied violence, harmful acts, or stereotypes reinforcement(see Álvarez-Cueva et al., 2021; Blaise et al., 2019). These representations are part of portrayals and lyrics in contemporary music production (Eze, 2020; López Maestre, 2021).

Sexism remains present nowadays to the extent that scholars discussed different forms of it, these are: benevolent (Good, 2017), hostile (Hack, 2017) and ambivalent (Grubbs, 2017). Either of these forms can be found at an institutional level (Capodilupo, 2017), interpersonal level or even internalized (Bearman & Amrhein, 2014). In line with this, Walter (2010) has discussed new 'guises' for old sexism resurgence among society. According to the author, society focuses the understanding of sexual allure on hyper sexuality. Indeed, from a post-feminist perspective, Gill (2011) argues that sexism operates through media while intersecting with other axes of power. She notes:

> [I]f we think about sexism not as a single, unchanging 'thing' (e.g. a set of relatively stable stereotypes), but instead reconceptualize it as an agile, dynamic, changing and diverse set of malleable representations and practices of power, how could it be anything less than urgent to have this term in our critical vocabulary? (…) sexism has not disappeared, but has taken on new forms. (Gill, 2011, pp. 62–63)

Indeed, to consider axes of power is to consider intersectionality (Crenshaw, 1989). This means, to include one or various levels of difference among research studies in order to highlight and problematize

how such differences impact on the many contradictions, significances and signifiers in society. In music studies, intersectionality has helped to dig on questions related to subjectivity e.g. in opposition to the assumed self-determination of sexualization (Álvarez-Cueva et al., 2021). In this sense, scholars' debates highlight how racialization, for instance, may have an implication when it comes to make sense of who is entitled of a portrayal (and its significance), and how such portrayals may have a different meaning based on racialization e.g. gender stereotypes.

Building on the studies presented above, the present work takes the position that women should not be subordinated to men, and that sexism remains a harmful pattern in cultural production, including music. In consequence, sexism is defined as a hostile and discriminatory practice/attitude towards (although not limited to) women and girls based on the axes of sex and the gender roles culturally linked and/or imposed onthem, due to the assumption that masculine attributes are superior to feminine. Moreover, such axes are no longer limited by sex and gender differences only, but to other levels of intersectionality where racialization may play a pivotal role to disentangle complexities about discrimination and oppression.

While this theoretical framework allows us to focus on the analysis of sexism against women, a disclaimer is in order. The present study is focused only on sexism towards women, incorporating an intersectional critical argumentation, not as a goal of the study itself but as an approach towards the findings that will enrich future works. Future work will be needed to untangle the nuances and implications of sexism from an intersectional approach.

Therefore, and far from entering in debates around sexuality and whereas its practice can be understood as a self-determined decision or not, this study includes a feminist perspective into the automatization of music lyrics analysis by (1) defining sexism – in line with previous feminist studies, as a continue practice of oppression towards women and femininity; and (2) moving the manual labeling and modeling to an automatization that may be replicated in future studies, as we explain in the next section.

Previous works on large-scale gender bias analysis in text

Computational methods have been used in previous works in the field of cultural studies to complement traditional methods of content analysis. We next provide some examples related to the study of music lyrics. Mahedero et al. (2005) evaluated Natural Language Processing (NLP) methods applied to music lyrics to identify language, structure, themes, or similarities between songs, and even genre classification by using a neural network architecture known as Bidirectional Long Short-Term Memory (BLSTM)(Araújo Lima et al., 2020). His initial findings on language identification, structure extraction, categorization, and similarity searches indicate that there is substantial potential for gaining insights and value from the analysis of lyrics. Emotion recognition in music lyrics has been achieved using similar neural network-based methods, such as word embeddings (Ara & Gopalakrishna, 2020), as well as detecting text reuse and similarities between artists (Meinecke & Jänicke, 2021). Explicit lyrics detection (lyrics that are not children appropriate) has been accomplished using other neural network-based methods including *FastText* and BERT, and sometimes methods not based on neural networks, such as logistic regression (Rospocher, 2021, 2023).

The study conducted by Barman et al. (2019) was the first to analyze bias and style using computational techniques on a huge dataset comprising five decades of music lyrics. They found that popular songs are quite different from other songs in terms of lyrics style, which suggests that lyrics are relevant factors of the popularity of a song. Furthermore, the authors observed that bias in lyrics corresponds to bias in humans. To do this analysis Barman et al. (2019) used a technique named Word Embedding Association Test (WEAT) with*word2vec* (Church, 2017) and *FastText*. Later, other studies (e.g. Gupta et al., 2021) have arisen following a similar structure and procedures to determine gender bias in songs.

Moreover, regarding specific Natural Language Processing (NLP) tools, word embeddings are widely used to detect sexism and gender bias across different types of text, from legal documents to social media. There are studies for sexism detection in law documents that use the WEAT approach, which computes the association of word lists that represent possibly biased issues to a set of pronoun or otherwise gendered pairs (Caliskan et al., 2017), has been used and proved to outperform current NLP bias detection methods (Gillis, 2021).

Many studies that use automated content analysis have focused on detecting sexism in social media, which remains as a concerning issue. The most common automated approach to detect sexism in these texts is by using BERT text embedding methods. This is the case of Butt et al. (2021), who attained a sexism identification F1 score of 78% using BERT, and Samghabadi et al. (2020), who achieved F1 score of 86% using the same method. Moreover, recently, a model for detecting misogyny in tweets has been described (Frenda et al., 2019), as well as a neural architecture based on BERT, which carried out the first work on multi-labeling classification for sexism detection (Parikh, 2019). Furthermore, there are in-depth analysis of sexist social media postings on social networking site Twitter/X (called 'tweets') that classified them as 'hostile', 'benevolent' or 'others' (Jha & Mamidi, 2017), using Support Vector Machines (SVM), sequence-to-sequence models and *FastText* classifiers (Joulin et al., 2016). Sharifirad and Matwin (2019) also used different types of word embeddings mixed with LSTM and Naive Bayes models to detect harassment of different classes.

Automated content analysis can also be used to perform longitudinal analyses of text, which are necessary as language changes over time, as new words appear, other words die, and the existing ones adopt additional meanings. Previous studies (Garg et al., 2018; Kozlowski et al., 2019) demonstrate that changes in word embeddings align with demographic shifts. Word embeddings are a potent tool for quantifying trends in social change, particularly in assessing the evolution of gender stereotypes and perspectives toward ethnic minorities (Garg et al., 2018). Additionally, research by Charlesworth et al. (2021) indicates that gender stereotypes consistently emerge in diverse language corpora.

All the surveyed papers use the same scheme: supervised text classification. In this scheme, a set of text passages are manually labeled according to whether each passage contains or not sexist expressions. Then, most of the manually labeled passages are used as 'training data' for an automated classifier, while the rest are used as 'testing data' to evaluate its accuracy. The automated classifiers used in previous research, as well as ours, start by converting the text to a vector representation (i.e. 'embedding' the text in a low-dimensional space), and then use statistical machine learning on the vectors. This usually yields high, but not perfect, classification accuracy. The main advantage of this automated method, compared to manual content analysis, is the reduction of the manual labeling cost and effort, which allows performing analyses at much larger scale. This is done at the expense of a reduction in accuracy with respect to manual labeling.

Materials and methods

Figure 1 overviews the study data processing, which includes data collection (§IV A), lyrics extraction (§IV B), manual labeling and modeling (§IVC), and automatic labeling (§IV D).

Data collection

The first step entailed data collection to identify the most popular songs in Spain from each decade spanning 1960 to 2022. This process resulted in a dataset containing song titles, artists, hit years, languages, and sources. Radical changes in listening habits during the observation period meant that different data sources were needed for different years. In this study, the authors used three sources for retrieving the most listened-to songs in Spain: the lists of *'Los40', 'Los Superventas'* and Spotify top songs. The obtained sample consisted of a total of 2910 songs. More detailed technical specifications are available in our repository: https://github.com/u161832/sexism_in_lyrics/.
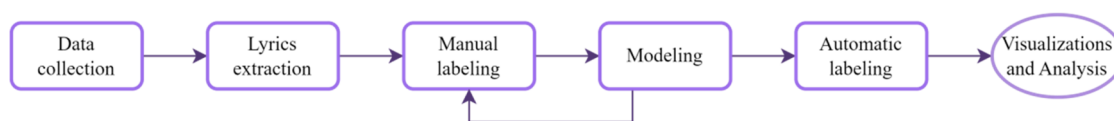

Figure 1. In this figure, the data processing stages are shown: data collection, lyrics extraction, manual labeling, modeling, automatic labeling, and visualization and analysis. An extra loop between manual labeling and modeling is included since this process was done iteratively.

Lyrics extraction

The second step was downloading the lyrics for the most popular songs identified. The majority were obtained using the Genius API (Genius Media Group, 2021), which is the largest collection of musical expertise and lyrical content worldwide, and the ones not found in the platform were downloaded manually. The authors completed the final analysis with 98.97% of the lyrics. The rest were either not located through manual Internet searches or were excluded during the automation process due to unconventional formats. Hence, the final sample to be analyzed consists of the lyrics of 2,840 songs.

Lyrics were parsed to divide them into paragraphs, yielding a total of 34,030 paragraphs, which served as the basic classification units.

Manual labeling and modeling

The process of manual labeling to obtain training data for machine learning modeling was undertaken in an iterative way, creating progressively more accurate models. To make labeling more efficient, each version of the model was used to stratify the sample of data to label for the next version.

New labels: sexist lyrics

A preliminary examination of the music lyrics analyzed by Parikh (2019) allowed the authors to build a list of common ways in which sexism manifested: role and attribute stereotyping, body-shaming, hyper-sexualization, threats, sexual assault, sexual harassment, victim blaming, slut-shaming, motherhood-related discrimination, physical violence, and gaslighting. Women objectification was also considered, which is seeing and/or treating a woman as an object (Papadaki, 2010); rape, defined as a sexual aggression involving penetration (Art. 192 Spanish Penal Code); and control and possession behavior, which involves sexist beliefs wherein men feel entitled to control or own women. This behavior encompasses paternalism, an ideology that instructs men to diminish women's agency (Ware, 2020). Examples of these categories can be found in the file 'Sexism_examples.md' of our repository.

Moreover, when uncovering sexism in lyrics, we examine how the concept of romantic love is depicted, with particular attention to the misguided belief that any action, including harmful or oppressive ones, can be carried out and justified in the name of love (Nava-Reyes et al., 2018). This misbelief can intersect with sexism against women when it perpetuates harmful stereotypes or normalizes behaviors that undermine the well-being, autonomy, or dignity of women. This study assumes that 'love' is not a valid justification for actions that perpetuate gender inequality or contribute to the mistreatment of women. Emphasizing the importance of healthy boundaries and mutual respect within romantic relationships is vital to counteract sexist ideologies present in lyrical content.

Learning scheme

The study's learning scheme is a supervised machine learning classification model that receives as input a paragraph of music lyrics, and outputs an inference on whether it contains or does not contain sexist language.

To simplify the task of text processing, song lyrics were broken down into smaller sections, referred to as paragraphs. These paragraphs were the ones that were labeled, not the entire songs. Only at the end of this process, after determining the number of sexist or non-sexist paragraphs within each song, were the songs themselves labeled. A song was considered sexist if it contained at least one paragraph labeled as sexist, this choice was driven by the understanding that a single instance can symbolize the overall tone and content of the song, influencing audience perception and shaping the song's message. The presence of even one sexist paragraph suggests sexist themes and reinforces harmful narratives, contributing to the normalization of discriminatory attitudes. While contextual considerations are crucial, the identification of sexism in a single paragraph serves as a point of entry for discussions about larger themes related to gender representation and the impact of such content on society.

Iterative modeling and labeling process

Three versions of the model were created. Each version was used to sample a varied set of paragraphs, which then were labeled manually. This manual annotation involved labeling the paragraphs as sexist/

non-sexist and indicating the specific sexism category present. For that, the established criteria for determining whether a paragraph was sexist or not, which is outlined in section §I, was followed. That is, a paragraph was considered sexist if it fits into one of the analytical categories of sexism against women aforementioned. If there was any doubt as to whether a paragraph was sexist or not, it was not labeled in order to avoid confusion in the training process. Annotations were done by one author of this paper and borderline cases discussed with another author of this paper. Examples of paragraphs labeled as sexist can be found in the file 'Sexism_examples.md' of our repository and paragraphs labeled as non-sexist can be found in the file 'Non_sexist_examples.md' of our repository. Among the paragraphs labeled as sexist in the final version of our training set, we can find the categories of sexism shown in Figure 2.

The source code of the model as well as detailed technical specifications and more examples can be found in the repository.

Automatic labeling

The machine learning model used was trained using the final manually created dataset. It achieves an AUC (Area Under the Curve) score of 92% and an F1 score of 84% (for explanations of these metrics, see, e.g. Hanley & McNeil, 1982; Van Rijsbergen, 1983). These scores reflect a high level of accuracy. We used this model to annotate the remaining, unlabeled paragraphs.

Crowdsourced data labeling

In parallel, the authors carried out two crowdsourcing tasks to gather information on how sexism is represented in lyrics. The focus was solely on Spanish songs, as they were the most prevalent in sexist songs, to ensure that the analysis would be more accurate. As aforementioned, the labeled dataset included a column with the categories of sexism present in each sexist paragraph.

We asked crowdsourcing workers to label the most prevalent categories: control and possession behavior, and hyper-sexualization (Figure 2). As hyper-sexualization and women objectification have similar definitions by theory, we decided to combine them. To gain a deeper understanding of these frequent categories and determine if there were any characteristic words that would differentiate between them, we used crowdsourcing to collect more labels.[2] Participants in the crowdsourcing effort were given a paragraph, along with a concise definition of the sexism category[3] and three examples from each category. The task was to classify the paragraphs (usually corresponding to song verses) as sexist or not based on the definition given. The task was completed by three different participants of the crowdsourcing effort and the results were used to create two datasets, a positive and a negative one for each category, containing respectively paragraphs that were labeled as belonging to the category and
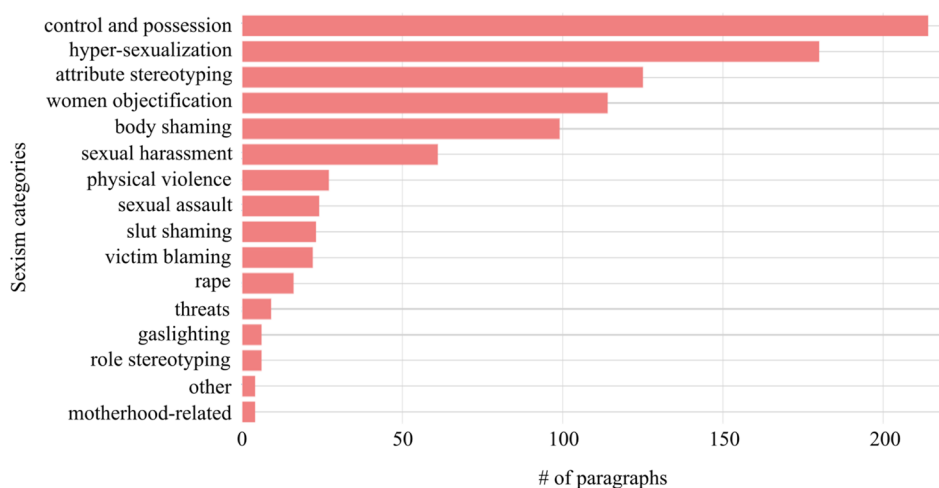

Figure 2. Sexism categories in the manually-labeled training dataset.

paragraphs that were not. These datasets were then used to create word shifts visualizations (Gallagher et al., 2021), which are shown and analyzed in §V D, to understand the words or phrases that are more prevalent in each sexist category. It is important to note that in all cases, there was a minimum of two-thirds agreement between the participants on the final answer used in the study.

Results

This chapter starts with the presentation of language prevalence in the dataset (§V A). Subsequently, percentages of obtained sexist songs are shown (§V B). Correlations are exposed, and frequent words found in sexist lyrics are studied (§V D and §V E). The prevalence of sexism in lyrics over time is then examined (§V C).

Prevalence of language

For the purpose of the present study, we gathered song lyrics to categorize them into sexist or non-sexist. As shown in Figure 3, 54% of the most listened to songs in Spain from 1960 to 2022 were in Spanish, while 45% were in English, and the remaining 1.5% were in other languages (i.e. Catalan, French, German, Galician, Hebrew, Italian, Korean, Portuguese, Xhosa and songs with both Spanish and English). Hence, we will only be focusing on songs in English and Spanish separately in the following sections, as they constitute the majority of the sample. It is worth noting, however, that many Spanish songs include English words due to the hybridization of language in music within the context of post-modernity, as the music industry is primarily concentrated in the global north, particularly in the US and the UK.[4]

Prevalence of sexism

In this section, we present the outcomes of the labeling process conducted on the lyrics of the most popular songs in Spain from 1960 to 2022, as illustrated in Figure 4.

Despite the possible common perception that only a negligible proportion of lyrics in the most listened songs in Spain over the past decades are sexist, our approach indicates that 51% of them are classified as sexist. In addition, out of the sexist songs, 60% are in Spanish and 38% are in English, whereas the rest are in other languages.[5]

Sexism over time

As illustrated in Figure 5(a), the automated labeling indicates that the prevalence of sexism has risen in recent years. Aside from the peak in the 70s, the level of sexism remained relatively stable until the 2000s. In the authors' opinion the most concerning result of this study is the sharp increase in sexism over the last two decades, which has surged to 77% of the analyzed songs. This implies that 77 out of the 100 most frequently played songs have lyrics that can be deemed sexist. Given the limited number of years of the last analyzed decade (2020, 2021, and 2022), the authors decided to conduct a more
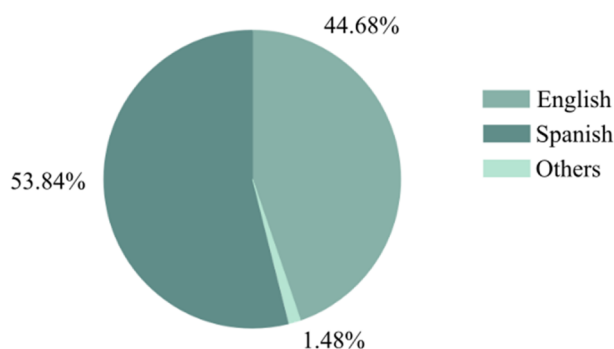

Figure 3. Percentage of languages of all songs represented in the final dataset.
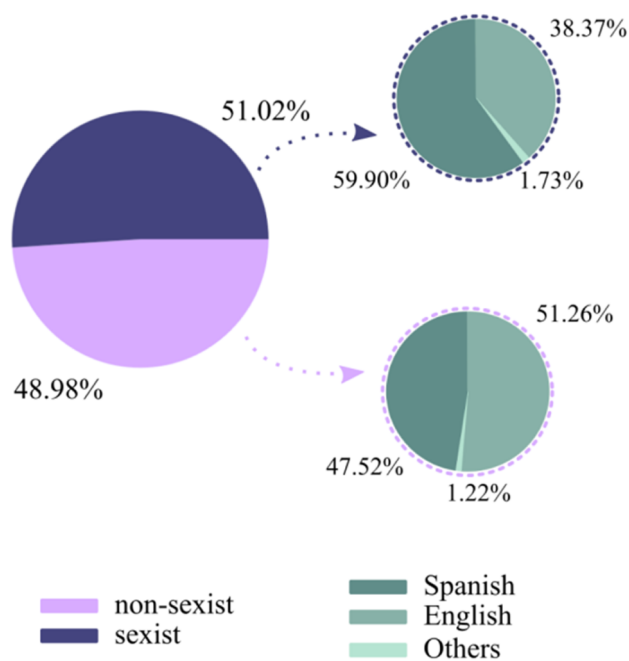
Figure 4. Percentage of total sexist and non-sexist songs. Also, percentage of languages for each category.
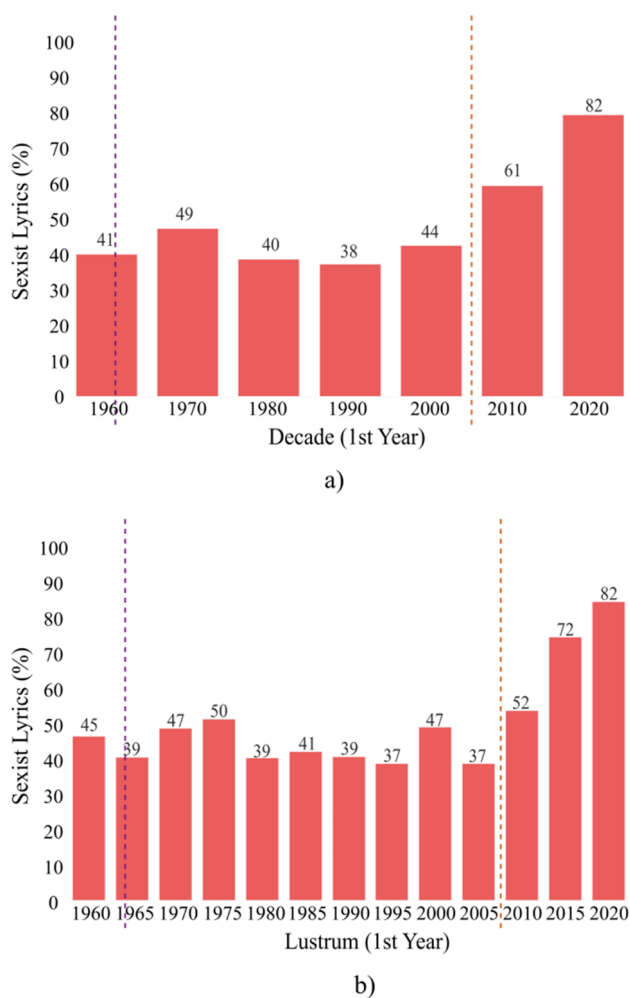

Figure 5. Top: percentage of sexist songs per decade. Bottom: percentage of sexist songs per lustrum. The vertical dashed lines separate the three data sources used to obtain lists of popular songs: "Los Superventas", "Los 40 Principales", and Spotify.

granular analysis by examining the progression of sexism in smaller groups of years. Therefore, Figure 5(b) displays the evolution of sexism in five-year periods since 1960. The proportion of sexist lyrics in the songs remains relatively constant between 37% and 50% during these periods until 2000. However, unlike in the previous examination, the trend remains consistent between 2000 and 2010. That is, between 37%and 53% of the lyrics contain sexism. With this visualization, we can more accurately determine that the primary increase in sexism in lyrics occurred during the 2015s.

Altogether, the results indicate that the most listened to songs in Spain have consistently contained sexist language throughout the years. Moreover, these results suggest that the prevalence of sexism in song lyrics has significantly increased in contemporary times compared to previous decades. A combination of future studies using different methods and different data samples are needed to strengthen this result. However, from our results, it is evident that the current popular music on Spotify tends to exhibit more sexist elements compared to what was popular on ‘Los 40 Principales’ and ‘Los Superventas’ in previous decades. This could have a more significant impact on listeners, particularly those who consume music through streaming platforms, which nowadays are the majority of people.

Frequent words in sexist lyrics

Word frequencies

We compared the most frequently appearing words in sexist and non-sexist lyrics. To achieve this, *scattertext* (Kessler, 2017), an open-source tool that generates comparative word-frequency scatterplots, was used. The frequency of words in the non-sexist set on the x-axis and the frequency of words in the sexist set on the y-axiswas plotted. Additionally, an interactive version of this plot, showcasing a list of the most frequent words for each category and the most characteristic ones overall, is available in the study's repository. The data plotted consisted of the 250 most common words in the entire dataset.

The relationship between vocabulary and sexism is illustrated in Figure 6 (for English) and Figure A1 (for Spanish, in the Appendix). This analysis highlights a group of words that have different frequencies in sexist and non-sexist paragraphs. It is important to keep in mind that these specific words were not used directly to categorize texts, as the categorization was done automatically based on manually annotated paragraphs. Instead, these words are more frequent in lyrics deemed sexist by the automated method. The most commonly used words in sexist paragraphs revolve around pleasure, women, the body, and sensual movements. Additionally, words like ‘crazy’ are more prevalent in sexist paragraphs than non-sexist ones. Conversely, the
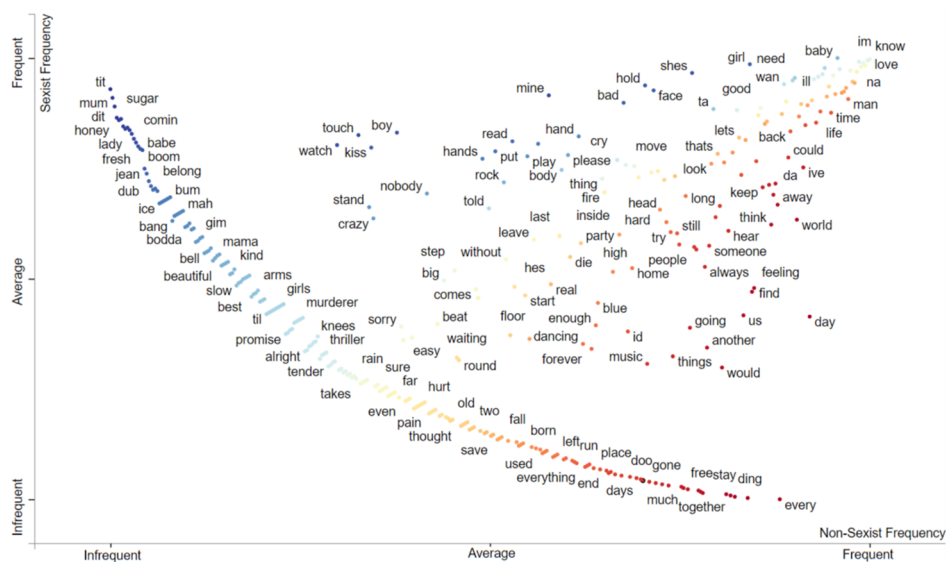
Figure 6. Most frequent words in sexist and non-sexist paragraphs in English. On the top left, colored in blue, there are the most frequent words in sexist paragraphs that are not frequent at all in non-sexist paragraphs. On the bottom right there are the least frequent words in sexist paragraphs that are hugely frequent in non-sexist paragraphs. Finally, in the top right, there are the words that are very frequent in both sexist and non-sexist paragraphs.

least frequent words in sexist paragraphs are associated with diverse states of mind, thoughts, dreams, life, and places to be in, which we could consider to be more poetic themes. Lastly, words related to love, but not explicitly to sexual acts, are frequently used in both sexist and non-sexist paragraphs.

Word shifts

The number of songs in each category of sexism within the manually labeled dataset was also inspected to identify patterns or characteristics that could aid in distinguishing between the categories.

To conduct this analysis, word shifts were used to measure the differences between the sets of words for each sexism category and the entire set of words in the sexist lyrics report. As described in section §IV.E, this is done using *shifterator*, a generalized word shift graph that visually compares frequent words between two sets of texts using a weighting measure. Specifically, proportion shifts[6] were used due to their simplicity and the fact that they are easy to interpret.

In Figure 7(a), the most frequent words in hyper-sexualized or objectifying language compared to the whole set of words in the sexist lyrics dataset, is presented using word shifts. Many of these words refer to the body or sexual acts and situations. It is worth reminding that while the lyrics analyzed where in Spanish, they sometimes borrow terms from English. For example, words such as *loco* ('crazy man'), *cuerpo* ('body'), *piel* ('skin'), *sabe* ('tastes'), *mojada* ('wet woman'), *culo* ('butt'), *duro* or *dura* ('hard'), and *'tas* ('you
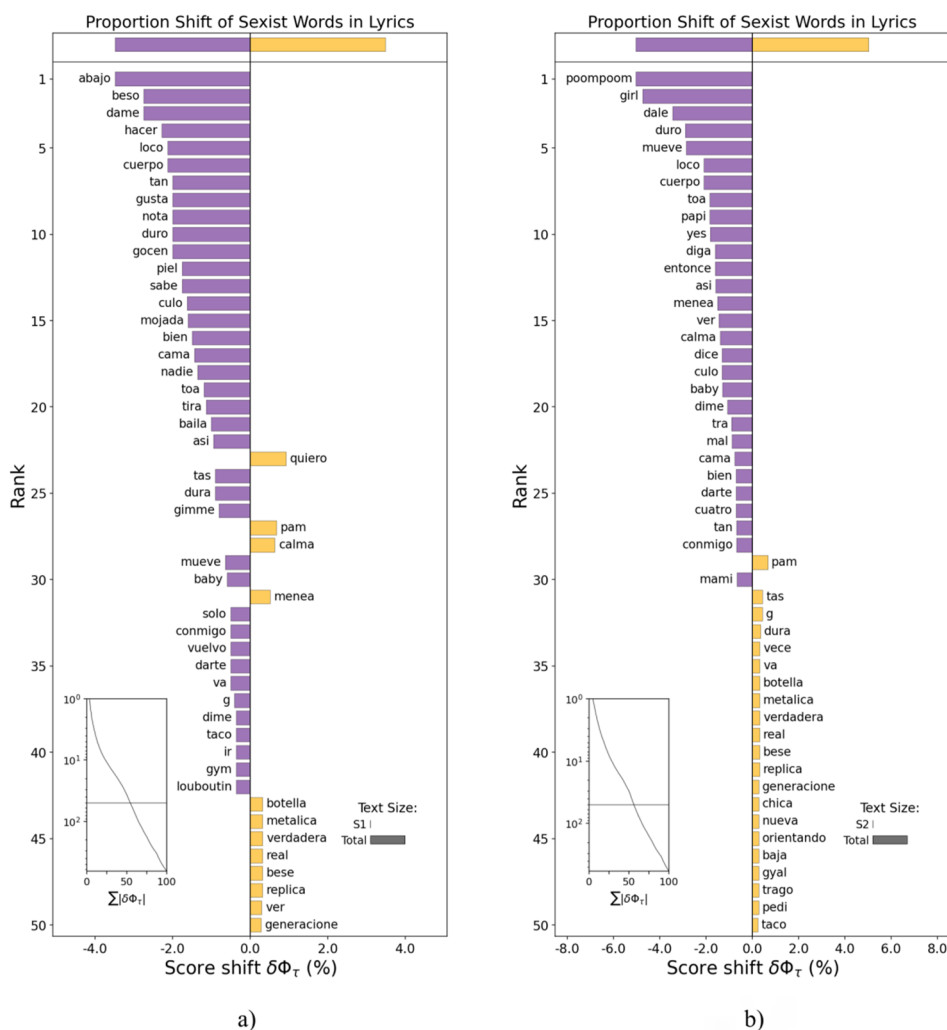
Figure 7. Word shifts (shifterator) of *hyper-sexualization and women objectification* (S1) and *control and possession behavior* (S2). a) *Hyper-sexualization and women objectification* most characteristic words compared to sexist characteristic words but non-characteristic of this category. b) *Control and possession behavior* most characteristic words compared to sexist characteristic words but non-characteristic of this category.

are'), refer to the body and often have a sexual connotation in the context in which they are used in sexist lyrics. Other words such as *beso* ('kiss'), *hacer* ('make'), *gocen* ('enjoy'), *gusta* ('like'), *cama* ('bed'), *gimme* ('give me'), and *darte* ('give you'), are oftenrelated to sexual acts in the context of sexist lyrics.

In the analysis of possessive and controlling language, Figure 7(b) shows the prevailing words in the entire set of sexist lyrics. Words such as *dale* ('give'), *mueve* ('move'), *menea* ('shake'), *poompoom* (referring to a twerk movement), and *dime* ('tell me') are frequent. These words are verbs in the imperative form and can be interpreted as commands given by a man to a woman to move in a certain way or say certain things. Additionally, words referring to the body and often having sexual connotations, such as *duro* ('hard'), *cuerpo* ('body'), *culo* ('butt'), and *cama* ('bed'), are common. Furthermore, the word *loco* ('crazy man'), which is often related to the idea that a woman's body drives a man 'crazy', also appears repeatedly.

Moreover, it is noted that the word *chica* ('girl') is not commonly used in Spanish lyrics to refer to a young woman. Instead, we observe the use of English words such as 'girl' or 'baby', as well as the diminutive *mami* (a term used to address one's mother).

Finally, it is pertinent to state that the terms listed in this section are some of the many ways in which sexism may manifest in some of the analyzed music lyrics. Sexism should not be solely reduced to words and phrases, and the automated content analysis takes some context into account. However, it has not reached human accuracy yet. Altogether, looking at some of these words helps us understand how sexism remains present in music lyrics.

Discussion and conclusions

Our main conclusions can be summarized as follows:

Sexism against women in has increased significantly in music lyrics, particularly since 2015

Overall, 51% of songs in the study's sample contain sexist expressions. While currently Spain scores relatively well compared to other EU countries in terms of Gender Equality Index,[7] historically sexism has been an issue (ABC, 2010, Solsten & Meditz, 1988) and the results are indicative of this historical context. According to the findings in this paper, sexism directed towards women in the most popular songs in Spain has increased significantly over the last twenty years, particularly since 2015. This happened simultaneously to streaming platforms overtaking radio as a means of listening music, making it challenging to ascertain whether the observed increase in sexism is a direct result or if it is influenced by the broader access to a large number of songs facilitated by streaming platforms.

Music is an artistic form of expression, and has an important role in both emotions and processes of identification and identity. Therefore, lyrics can be a tool for positive social change. This is not to fall into a naive view, but to critically describe how cultural production portrays and relates to the society. The increased prevalence of sexism in the last decade might be disappointing considering the impact that feminist movements have had recently in Spain, particularly the massive demonstrations for International Women's Day in 2018, 2019, and 2020. The music lyrics we have analyzed do not show a less sexist society; on the contrary, they suggest that Spanish society still has a vast amount of sexism in it. These findings go in line with other studies regarding sexism and gender violence (Ministerio de Igualdad, 2023).

Streaming platforms hold power over what users listen (Prey, 2020). However, the authors consider that this power is exercised in a different manner in a streaming platform compared to when a radio DJ in the past selected tracks for a music program. The number of choices of users is vastly different, and hence control over the listening experience of users is reduced. This may reduce editorial control over explicit and controversial materials, including sexist lyrics. Moreover, algorithms fueled by user consumption patterns may contribute to feedback loops in which the dissemination of sexist lyrics is perpetuated.

Sexism is expressed as both controlling and possessive behavior, and hyper-sexualization, in music lyrics

Consistently, prevalent words used in sexist-tagged songs revolve around pleasure, women, the body, and sensual movements. Additionally, the most frequent terms used for controlling and possessing

behavior are imperative verbs, while for hyper-sexualization and objectification of women the most commonly recurring words pertain to sexual acts or circumstances.

The increase in sexism observed in music lyrics happens within a context of increased societal concern in Spain about sexism and gender violence (Ministerio de Igualdad, 2023). It implicates society at many layers and is clearly visible in music lyrics. This points out that sexism is systemic, and ending sexism requires the involvement of various societal actors at many levels.

Limitations and future research

First, since this study is the first attempt to gather sexism in a study focused on contemporary music in Spain, the codification presented a challenge. Datasets of texts labeled for sexist expressions were available from previous works, but for entirely different domains (such as social media) and were neither sufficient nor adequate for our purposes. While most lyrics were labeled/reviewed by authors of this study, this research also employed crowdsourcing during labeling to mitigate this problem. However, a broader sexism labeling exercise would greatly contribute to performing more accurate categorization of lyrics, and thus obtaining more precise statistics.

Second, before training any model with a dataset, data cleaning is usually performed. Lyrics are usually written in an informal way, and transcriptions are normally user-generated and unofficial. Songs are often made to be sung and not to be read. Thus, they are made of spoken vocabulary and its text is commonly not grammatically correct, which makes them harder to read. In addition, there are elements that appear in the lyrics such as sounds or onomatopoeia that are hard to parse and interpret. Therefore, during the study the authors find some informal words and expressions which sometimes hamper the procedure and the analysis.

Third, categorizing a song as sexist based on the presence of sexism in a single labeled paragraph may not be the most accurate approach as it disregards the broader context. Given the significant advancements in natural language processing (NLP) today, it would be desirable (but challenging) to develop a classifier trained on complete songs to retain all the necessary context and provide more nuanced analysis. More generally, while automatic annotation of text allows the processing a quantity of text that one would not be able to annotate manually given our resources, as said earlier, the authors recognize that this process is sensitive to some extent to noise and bias, while providing a solid starting point for further exploration.

Fourth, the automatization of the lyrics gathering part could be improved to avoid losing data and save time when doing things manually. We were not able to download about 2.7% of the songs automatically, possibly due to differences in the way their title was written, or to text coding errors. However, if we look by decade, the ones with fewer failures to download music lyrics were the last two, which means that our results would not be substantially different as these decades are also the ones where sexism was more observed.

Fifth, gender bias in word embeddings is well documented and may affect our classifier results. There is an active research direction exploring how to mitigate this impact effect (Bolukbasi et al., 2016, Brunet et al., 2019, Dev & Phillips, 2019, Schmahl et al., 2020, Swinger et al., 2019).

Finally, taking an intersectional approach, additional research that explores whether the lyrics make references to racialized bodies could contribute to a more nuanced analysis. However, achieving this would require a systematic effort to obtain a large set reflecting racialization in music lyrics.

Notes

1. Hereafter, feminine along the study will be mostly used to refer to women, as the main goal is to explore sexism against them. Moreover, in this research "sexism" refers to sexism against women, unless specified otherwise. Whenever the reader finds the term "feminine", it refers to the sexist definition of feminine against masculine, where the latter is defined in opposition to the former, and assumed to be better.
2. The crowdsourcing platform used was Surge HQ, more information can be found in https://www.surgehq.ai/.
3. Note that the definition for the combination of hyper-sexualization and women objectification was rephrased as follows: *Unwarranted focus on women physical aspects or sexual acts, or seeing and/or treating a woman, as an object or animal.*
4. 2021 music industry statistics: https://gmr2021.ifpi.org/assets/GMR2021_State%20of%20the%20Industry.pdf.

5. The other languages were: African, Catalan, French, German, Galician, Hebrew, Italian, Korean, Portuguese, Xhosa and songs with both Spanish and English.
6. See more in detail here: https://shifterator.readthedocs.io/en/latest/cookbook/frequency_shifts.html.
7. https://eige.europa.eu/publications/gender-equality-index-2021-health.

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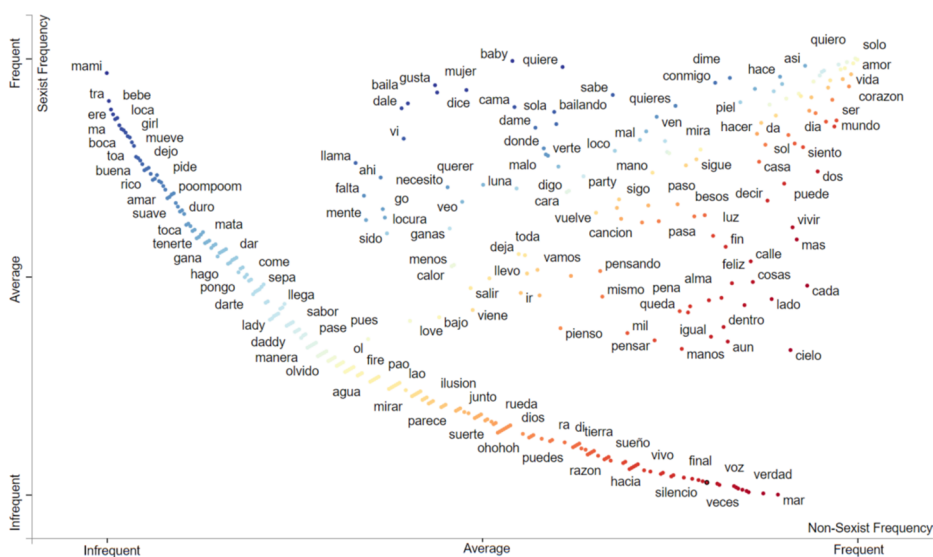
Appendix

Figure A1. Most frequent words in sexist and non-sexist paragraphs in Spanish. On the top left, colored in blue, there are the most frequent words in sexist paragraphs that are not frequent at all in non-sexist paragraphs. On the bottom right there are the least frequent words in sexist paragraphs that are hugely frequent in non-sexist paragraphs. Finally, in the top right, there are the words that are very frequent in both sexist and non-sexist paragraphs.