a sparse matrix representation of Page Likes per user and applied sparse singular value decomposition to reduce dimensionality, while binning the age attribute (median = 25) as "younger" (< 25) and "older" (≥ 25) allowed to approximate the official census distribution [45]. We then employed an XGBoost classifier, to predict missing age values [35], with an estimated $AUROC = 0.79$ and standard deviation $= 0.018$. Acknowledging that age inference might add bias to our models, we only use age as a predictor in isolated experiments (see Table 4). We also run the same experiments keeping only users who provided their age. Predictions were similar for Binding and slightly lower for Individualising.

To ensure the stability of our regression models, we applied a simple activity threshold. After extensive experimentation we chose to drop users with less than 10 Facebook Page Likes related to music artists (Page category selection), resulting in a reduced final dataset of 1,386 users. Table 1 reports the demographic breakdown of our data sample in terms of gender and age, which follows closely the population distribution of the official Italian census [45].

For the final 1,386 users, we retrieved song lyrics corresponding to their music artist Page Likes using *genius.com*. Querying the Genius API, we initially obtained the 10 most popular songs per artist alongside the respective lyrics. We assume that if a user liked the Page of a specific artist, then that artist's most famous songs (as per Genius) reflect the music preferences of the user. We carried out predictive tasks using the n = 10, 5, or 3 most popular songs from an artist and found that n = 5 gave the best compromise in terms of predictions, computational resources, and within-musician variability in lyrical and audio content (see future work discussion) while maintaining an optimal number of musicians and songs for our lyrics data. Finally, we used the spaCy library [47, 48] to identify songs with English lyrics only, resulting in 3,179 artists and 15,895 songs.

We also considered two additional, more shallow digital trace features that can potentially convey information about user's music habits, namely the number of Page Likes per user (mean $= 35.11$, standard deviation $= 33.95$) and a built-in feature of artist popularity from LikeYouth, based on the number of Page followers.

We use LikeYouth because, to our best knowledge, it is the only dataset providing MFT scores of individuals alongside a potential proxy of their music preferences (e.g., artist Page Likes). A limitation of this approach is that the data provided by LikeYouth are static and may thus refer to a snapshot of music interests in time. Streaming platforms could offer richer information about habitual music listening [7, 42]. Nonetheless, there is substantial evidence that Facebook Page Likes can capture personality needs and personal values [5, 20, 46]. Another limitation is that LikeYouth user MFT scores and thus our predictive models cannot be made publicly available due to privacy implications [34]. Instead, we have shared the lyrics data and related source code for lyrical feature modeling in a GitHub repository. [1]

[1] https://github.com/vjosapreniqi/lyrics-content-features

Type	Method	Features
Topics	LDA	Death/Fear/Violence, Obscene, Romantic, World/Time/Life
Morals	MoralStrength	Care, Fairness, Loyalty, Authority, Purity
Sentiment	VADER	Negative, Positive, Neutral, Compound
Emotions	NRC	Anger, Disgust, Fear, Sadness, Anticipation, Surprise, Joy, Trust

Table 2. Summary of lyrical features used in this study.

4. LYRICS CONTENT ANALYSIS

We extracted a set of textual features related to each song lyrics' overarching narrative (topic modelling), moral valence, sentiment, and emotion. Based on the corresponding feature modeling method, we applied different levels of text preprocessing. Sentiment detection required only a general cleanup while keeping punctuation and capitalization within the text. For the other methods, we extracted Part Of Speech (POS) lemmas using the spaCy lemmatizer [47]. On average, each lyrics contained 273 words and 108 lemmas.

4.1 Topic Modelling

Initially, we aimed to uncover common patterns in the lyrics narratives by applying a topic modelling approach based on Latent Dirichlet Allocation (LDA) [24]. We used LDA due to its simplicity, high accuracy in topic modelling, and good computational efficiency [49]. The input of the LDA model is a term frequency matrix of the corpus created by the song lyrics. To eliminate very common terms that can lead to irrelevant topics, we ignored words with frequency higher than 90%.

To derive the optimum number of topics k, we optimized the topic coherency (C_v metric [50]) for models with $k \in [2, 16]$ using a step size of 2. The number of topics for which coherency was maximised was $k = 4$. For $k > 4$, we obtained topics that were either generic or hard to characterise due to the mixture of different words belonging to multiple topics. While for $k = 4$, the topics obtained were in line with previous literature [51,52]. Table 3 depicts examples of manually selected songs of 5 artists for each topic, ranked by descending weight in the specific topic.

4.2 Moral Valence

We assess the moral narratives by employing the MoralStrength lexicon [23], which holds the state-of-the-art performance in moral text prediction. This expands the Moral Foundation Dictionary by offering three times more moral-annotated lemmas. The lexicon provides, along with each lemma, the *moral valence score*, a numeric assessment that indicates both the polarity and the intensity of the lemma

Topic	Artist	Song Title	%
Romantic (0.39)	Mike Williams	Give it up	99
	Marc Anthony	I need to know	99
	NSYNC	I want you back	99
	Willie Nelson	Always on my mind	98
	Alexia	Because I miss you	97
Obscene (0.24)	Tyga	Rack city	98
	Fat Joe	Yellow tape	96
	Cardi B	Bartier cardi	95
	Chamillionaire	Ridin'	95
	21 Savage	Bank account	91
World/Time/ Life (0.22)	Holly Herndon	Morning sun	99
	Noisecontrollers	The day	97
	Nathan East	Finally home	96
	Dave Gahan	Tomorrow	94
	Gabrielle Aplin	Start of time	90
Death/Fear/ Violence (0.15)	Hatebreed	Destroy everything	99
	Fear Factory	Edgecrusher	97
	Eomac	Mandate for murder	95
	Destruction	Thrash till death	92
	Sabaton	Attack of dead men	91

Table 3. LDA topic modelling: overall topic prevalence (in brackets below topic descriptions) and 5 manually selected songs per topic as ranked by descending topic proportion.

in each of the five moral foundations (MFT traits). Moral valence is expressed on a Likert scale from one to nine, with five considered neutral. When lower than 5, scores reflect notions closer to Harm, Cheating, Betrayal, Subversion, and Degradation, while values higher than 5 indicate Care, Fairness, Loyalty, Authority, and Purity, respectively.

We obtained a moral valence score for each lemma in a song's lyrics and each MFT trait, which is then averaged across lemmas for each song. Negation correction was not applied, as moral foundation polarities do not directly translate as opposites (e.g., "not care" is not the same as "harm"). The MoralStrength lexicon has a limited linguistic coverage; as a result, we could not predict moral valence for 16% of the collected lyrics. Instead, we assigned them the value 5, the neutral point of the moral valence Likert scale. This approach pushes the observed mean towards the center of the scale, but captures the variability of the moral values across all the lyrical data.

4.3 Sentiment and Emotion Analysis

In textual data, emotions, as brief and preconscious phenomena, can be defined via descriptions of appraisal, physiological reaction, expressive display, feeling, or action tendency, while sentiments, as lasting and conscious emotional dispositions, tend to be modelled in terms of text polarity (positive, negative, neutral) [53].

We applied the commonly used VADER (Valence Aware Dictionary and sEntiment Reasoner) model [21] on the lyrical text to obtain information about the sentiment of each song. The VADER model is shown to perform well both with long and short text, providing for each song a score for positive, neutral, negative, and compound sentiment

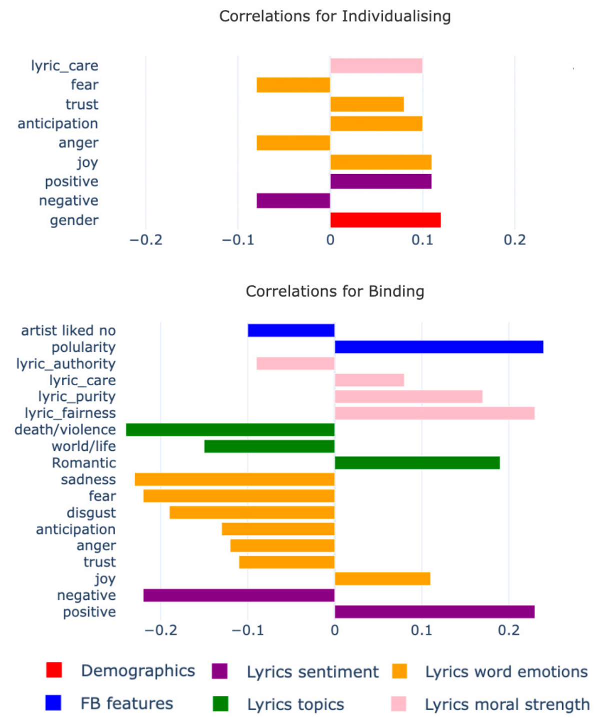

Figure 1. Spearman's Rank correlations of MFT super foundations with demographics, artist likes and lyrics features. We report only ones that were significant at $p \leq .01$. "Artist liked no" refers to the number of artist Likes per user.

(see Table 2). We also estimated the eight basic emotions defined in the Plutchik wheel of emotions [54] employing the NRC Word–Emotion Association Lexicon [22]. This lexicon was shown to be efficient with unlabeled data [55]. Each song lyrics was annotated with the eight emotions (see Table 2) by averaging its word emotion association scores.

5. EXPERIMENTS AND RESULTS

Initially, we explored the relationship between users' moral values as emerged from the self-reported questionnaires, basic demographic attributes, and their respective music preferences, as expressed in the linguistic components of the lyrics. Figure 1 depicts the statistically significant correlations ($p \leq .01$) obtained for the two superior foundations, namely Individualising and Binding. We observed that people who value more Individualising foundations prefer artists whose songs prevalently talk about anticipation and trust. On the other side, those concerned more about social order and Binding foundations tend to prefer artists who deal with more romantic topics in their songs instead of existential and social issues. Overall, participants with strong Binding foundations display a tendency to dislike songs with negative valence and emotions such as sadness, fear, or disgust. Yet both the Individualising and Binding groups resonate with positive and joyful songs, showing that despite often profound differences in sociopolitical stances, music is a shelter to everyone.

Next, we proposed a series of experimental designs to

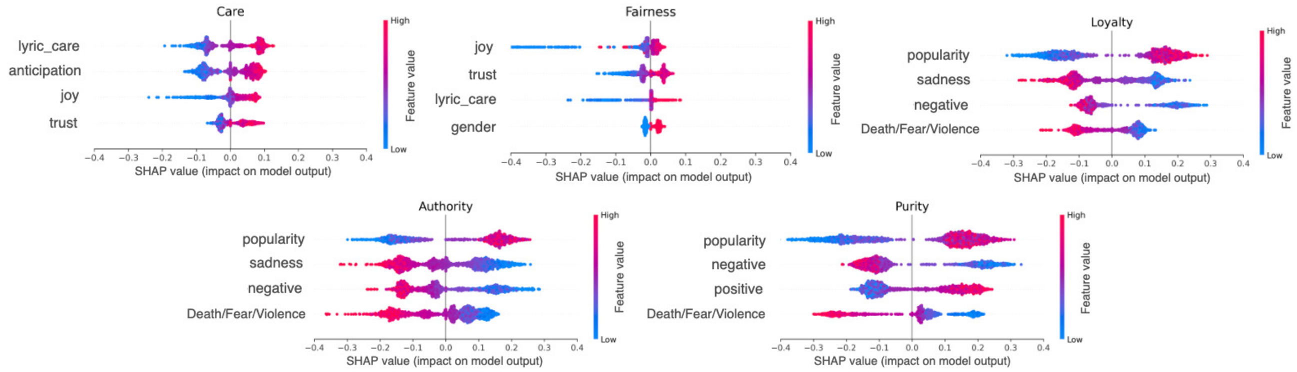

Figure 2. Top 4 individual feature contributions (via SHAP values) for the five basic moral foundations from experiment EX8 (see Table 4). The higher the SHAP value, the more the feature contributes to the prediction model.

ID	**Features**
EX1	Sentiment (VADER)
EX2	Emotions (NRC)
EX3	Sentiment + Emotions
EX4	Best of {EX1, EX2, EX3} + Morals
EX5	Best of {EX1, EX2, EX3} + Topics
EX6	Best of {EX1, EX2, EX3} + Morals + Topics
EX7	EX6 + Age + Gender
EX8	EX7 + Artist Likes + Artist Popularity

Table 4. Summary of performed experiments with corresponding features used as predictors.

infer moral values of the participants from their music preferences and the respective linguistic content. Table 4 summarises the performed experiments. We employed four algorithms, namely Support Vector Regressor, Random Forest, XGBoost, and ElasticNet, to predict moral values using a multivariate regression approach over a 5-fold cross-validation setting. For each participant, the features were aggregated and normalised. Here, we report only the results from the Random Forest since it slightly outperformed the rest. We used the Pearson's correlation coefficients between the predicted and actual moral values scores to measure the model's goodness fit. This metric was commonly used in papers that predicted personality based on users' music preferences and listening behaviours [5, 56].

To comprehend the general behaviour of our models and evaluate the importance of each feature, we estimated the SHAP values. SHAP (SHapley Additive exPlanations) is a game theory approach designed to illustrate the features' contribution to the final output of any machine learning model [57].

Following the incremental experimental design reported in Table 4, we trained one model per each moral foundation and presented the best results obtained by each feature in Table 5. In line with recent literature [25] that shows higher prediction accuracy for Binding rather than Individualising foundations, we noticed a similar behaviour also when inferring from linguistic features of song lyrics.

When adding demographics and artist Facebook information (EX8), the results slightly improved for both super foundations, implying that the more information we have about users' demographics and music preferences, the more precise our models become. Despite that, the model trained on just emotions, sentiment and moral information (EX4) achieved almost as good results as those who are aware of the demographics and the general artist information (EX7 and EX8). This highlights the importance of music preferences in portraying our goals and decisions whose motivations go far beyond basic demographic knowledge.

Figure 2 depicts the most important individual (only top 4 due to page restrictions) features for predicting each of the five moral foundations. While Figure 3 illustrates the impact individual (top 8) and grouped features in inferring the two superior foundations when considering all predictor variables (EX8). In line with observed correlations, feature importance representations for regression models show that lyrics linked to objective and subtle emotions (e.g., joy, trust, and anticipation) effectively predict Care and Fairness. Whereas more intense and opposite polarities of sentiment and emotions (e.g., fear, sadness, lyrics positive and negative valence) account for better predictions of Loyalty, Authority and Purity. We noticed that those who value more the Binding foundations appear to be sensitive to the popularity of the song, which reflects their worldview of prioritising group-focus over self-focus.

6. CONCLUSION

This paper discussed the link between lyrical information and moral values. We presented a wide range of lyrics processing techniques and features for measuring the power of linguistic aspects in predicting complex psychological traits such as moral values. Besides, we explored and compared the impact of user demographics and shallow digital traces in inferring moral foundations against the song lyrics components.

We noticed that Binders express their views throughout their music preference and lyrical styles. In contrast, Individualising views are more complex to be captured solely by people's music lyrics preferences. Thus, using the proposed framework, it was easier to infer moral values of Binding

	Moral Foundations - Regression Models							
	EX1	EX2	EX3	EX4	EX5	EX6	EX7	EX8
C	.08 [.08, .09]	.10 [.10, .11]	.10 [.10, .11]	.11 [.11, .12]	.10 [.10, .11]	**.12 [.11, .12]**	**.12 [.12, .13]**	.11 [.11, .12]
F	.04 [.04, .05]	.06 [.05, .06]	.05 [.04, .05]	.06 [.05, .06]	.06 [.05, .06]	.05 [.05, .05]	**.08 [.07, .08]**	.05 [.05, .05]
L	.12 [.12, .13]	.16 [.16, .17]	.18 [.17, .18]	**.20 [.20, .21]**	.19 [.18, .19]	.19 [.19, .20]	**.20 [.20, .21]**	**.20 [.20, .21]**
A	.19 [.19, .19]	.21 [.21, .22]	.23 [.23, .24]	.26 [.26, .26]	.24 [.24, .24]	.25 [.25, .26]	.26 [.26, .26]	**.27 [.26, .27]**
P	.19 [.18, .19]	.20 [.20, .21]	.24 [.23, .24]	.25 [.25, .26]	.23 [.22, .23]	.25 [.24, .25]	.24 [.24, .25]	**.26 [.26, .26]**
I	.08 [.07, .08]	.10 [.10, .11]	.10 [.10, .11]	.10 [.09, .10]	.09 [.09, .10]	.10 [.10, .11]	**.11 [.10, .11]**	.10 [.10, .11]
B	.20 [.19, .20]	.24 [.23, .24]	.26 [.26, .27]	.28 [.28, .29]	.26 [.26, .27]	.28 [.27, .28]	.27 [.27, .28]	**.30 [.30, .31]**

Table 5. Moral foundations regression with Random Forest using different feature combinations (see Table 4): Pearson's correlation [95% confidence intervals] between predicted and the actual values averaged across 5-fold cross-validation. C: Care; F: Fairness; L: Loyalty; A: Authority; P: Purity; I: Individualising; B: Binding.

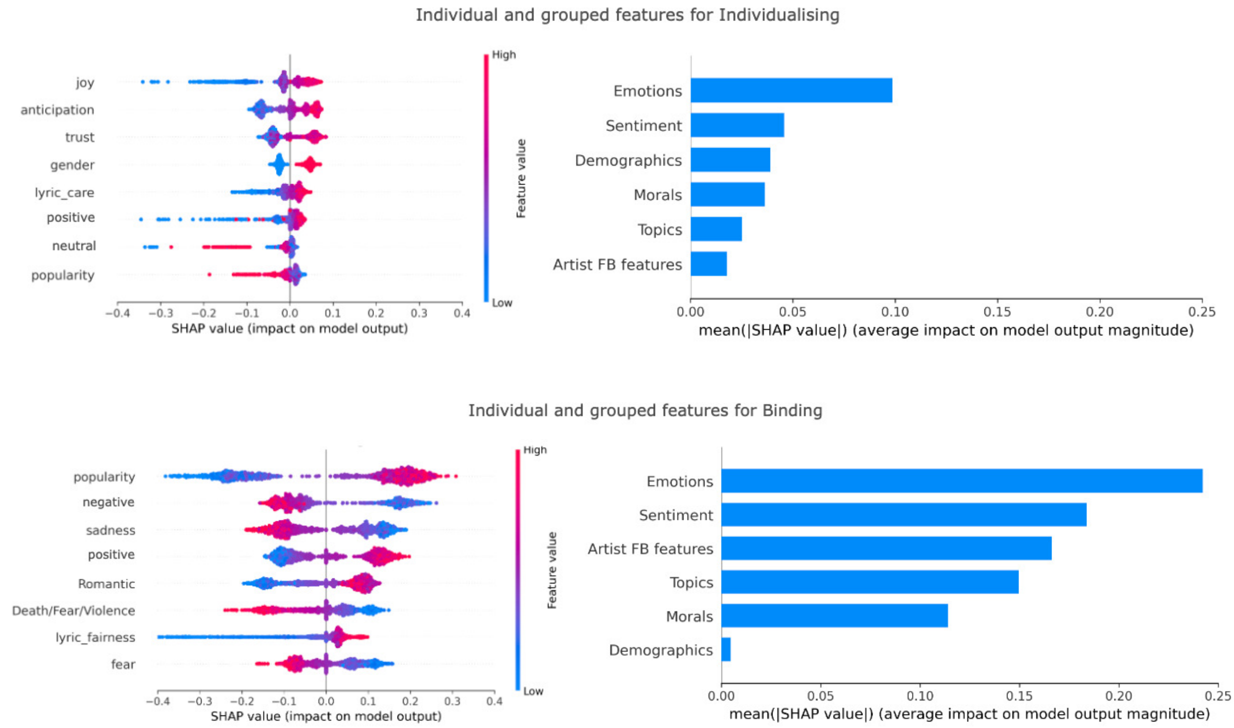

Figure 3. Individual (top 8) and grouped feature contributions (via SHAP values) for the two superior moral foundations from experiment EX8 (see Table 4). The higher the SHAP value, the more the feature contributes to the prediction model.

($.20 \leq r \leq .30$) between predicted and target values than Individualising foundations ($.08 \leq r \leq .11$).

We demonstrated that lyrics features extracted from the naturally emerging music preferences in social media, to some extent, allow for constructing reliable inferences of moral values. Considering the expanded presence of online music streaming services our findings may have direct implications for music recommendation and personalisation algorithms [1,5,58]. Since moral values are a key element of the decision making process in several societal issues [35, 59] and highly linked to political leanings [60], our research implications can help future studies to tackle aspects of why and how music is or can be used for mass stimulation and persuasion in social and political campaigns, raising awareness on what our digital music behaviours can reveal.

In future work, we intend to combine audio and lyrical content analysis together in a multimodal framework to further expand our understanding of music and moral affiliations, especially for Individualising foundations that remain hard to predict. Recent work highlights that preferences for both lyrics and audio features are important in predicting, often distinctly, personality traits [42]. We will also use additional data from LikeYouth to investigate if moral foundations can explain variance in music preferences that cannot be accounted for by personality traits and personal values (cf. [26]). We ultimately aim to integrate our findings into novel psychologically aware music recommender systems, but also beyond the music domain to other media.

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