Global music discoveries reveal cultural shifts during the war in Ukraine

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Collective engagement with culture including music and the arts can trace societal changes associated with acute disruptions, such as pandemics, political movements, and wars[1–7]. Can the daily shared experiences of culture reveal deep and long lasting societal impacts of disturbances? We collected longitudinal data of 12.8 million music discoveries via Shazam across 1,423 cities and 53 countries, relating them to the onset of Russia's invasion of Ukraine in 2022. Among post-Soviet countries, results revealed cascades of societal disintegration that rapidly escalated during the invasion. Initially similar music discoveries across countries broke down into distinct clusters that persisted over months. Cultural shifts were asymmetric: Ukraine saw a stark rise in the discovery of local, patriotic music, while Russia experienced a moderate decrease in their local music. At the city-level, socio-cultural values predicted subnational changes in music discovery inflicted by the war, bringing to surface latent variations within Ukraine and Russia. Interestingly, in Belarus, despite their political alliance with Russia, discoveries of Russian music decreased while Ukrainian music increased, suggesting undercurrents and resistance. Our work provides insights into the interactions between culture and society, revealing the pathways through which societal disruptions imprint the evolution of culture.

Main

War generates one of the most severe forms of disruption and instability in the social fabric. The Russian invasion of Ukraine on February 24, 2022, caused a large-scale humanitarian crisis[8], with more than 7 million Ukrainian refugees[9] and many civilian casualties[10]. As this conflict unfolded, the impact of war extended into other domains of daily life, from the expression of public opinions and emotions on social media[11–18] to psychological well-being and trauma[19–21]. How did this shockwave spread along temporal and spatial cultural threads across cities and countries? Can we use culture to probe societal changes in real-time?

Tracking engagement with music can be particularly useful for probing such changes. Transcending its roles as art and entertainment, music can serve as a marker of cultural evolution, echoing changes in group identities, values, and collective experiences[5,22–26]. The advancement of mobile technology now allows for the global tracking of music engagement across both private and public domains[4,27–30]. This unprecedented opportunity enables us to capture global patterns of collective engagement of music in high spatio-temporal resolutions, even amidst highly disruptive events like war, where collective human behavior can provide insights into the resilience and shared experiences of people facing life-threatening situations[2,3,31,32].

To understand the interaction between culture and social disturbances, we harnessed a dataset of 17.8 million top-searched songs from the mobile application Shazam across 1,423 cities in 53 countries (Fig. 1a). Shazam uses audio fingerprinting techniques for users to quickly identify unfamiliar songs playing in their immediate surroundings[33]. Importantly, Shazam discoveries reflect music actually played in the open air and require individuals to actively seek information about the song. This is in contrast with passive metrics such as *likes* on social media, making it a uniquely powerful lens to probe collective cultural engagement. We make this data and analysis scripts publicly available (Data and code availability) along with an interactive version at https://musicdiscover.net.

Rapid cultural shifts in post-Soviet countries following the invasion

We began by examining changes in music discovery patterns around the world (Fig. 1a), comparing the three months preceding and following the Russian invasion of Ukraine on February 24, 2022. We first computed the daily similarity of song discoveries among the countries (i.e., their shared repertoire) for each world region (World regions and Discovery similarity in Methods). Fig. 1b shows a rapid decline in similarity between countries within the post-Soviet region. This decrease in similarity began at least three months prior to the invasion (Generalized Additive Models (GAM) coefficient three months prior to invasion = -0.008, 95% CI = [-0.011, -0.006], $p < 0.001$ via bootstrapping) and rapidly accelerated during the first month of the conflict (GAM coefficient = -0.04 [-0.05, -0.02], $p < 0.001$). Among all world regions, the post-Soviet region showed the strongest decline in similarity, reflecting a process of cultural disintegration and divide between its countries (Fig. 1c; Cohen's d = -2.26 [-2.51, -2.03], $p < 0.001$). Europe, on the other hand, exhibited a moderate but significant rise in discovery similarity (d = 0.27 [0.14, 0.41], $p < 0.001$), suggesting closer cultural ties among the European countries.

We next tested whether the cultural impact of war affected the global structure of music influence and diffusion. Using a network inference model[34], we constructed a city-level diffusion network based on the global song propagation patterns over time (Network inference in Methods). By taking into account the temporal trajectories of songs as they become popular across cities (i.e., extensive discovery by a vast audience), this model infers directional pathways of music diffusion (edges) between cities (nodes). Fig. 1d,e show the global network of music diffusion before and after the invasion using N = 79,310 song cascades (Network visualization in Methods).

While the global structure of the network remained generally stable after the invasion (r = 0.803 [0.802, 0.804], $p < 0.001$, Supplementary Fig. 1), there was a stark shift within the post-Soviet region (Figs. 1d,e), where the number of network edges among the post-Soviet cities significantly decreased after the invasion by -26.76% [-27.52, -26.00]. The magnitude of this change was more than doubled that observed in any other region (Supplementary Fig. 2). Prior to the conflict, post-Soviet cities were densely interconnected across national boundaries, forming a highly homogeneous cultural cluster (Fig. 1d inset), but following the invasion, these cities became culturally distant from those in other countries, fragmenting into distinct national clusters (Fig. 1e inset). This is consistent with our previous observation of the decrease in discovery similarity among post-Soviet countries (Figs. 1b,c). We also found the same fragmentation of clusters using a simpler method based on co-occurrence of music discoveries across city pairs (Network validation in Methods; Supplementary Fig. 3).

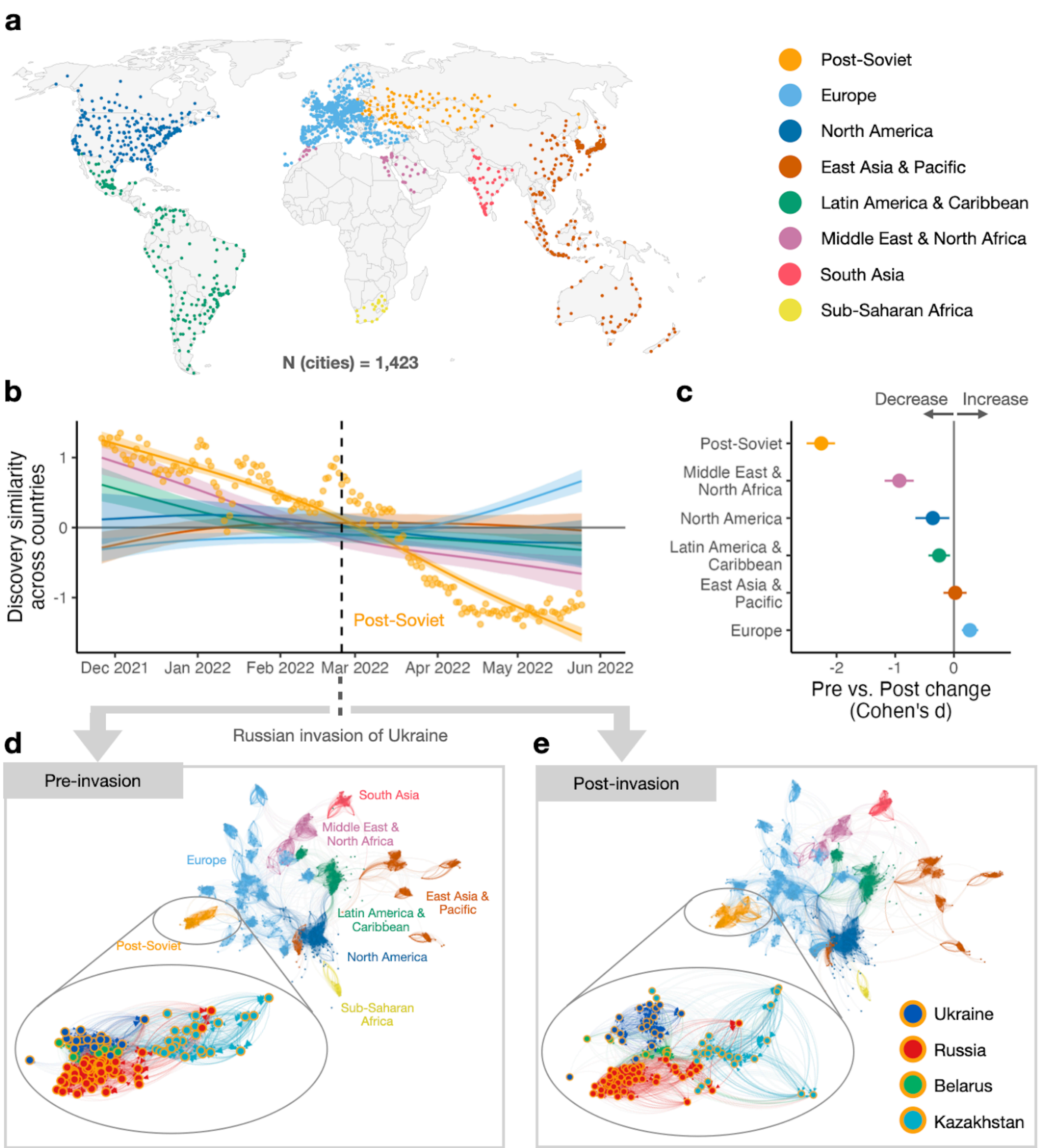

Fig. 1: Global music discoveries reveal rapid and drastic cultural shifts in post-Soviet countries following the 2022 Russian invasion of Ukraine.

(a) Global music discovery data across 1,423 cities and 53 countries (dots represent cities, color-coded by world region). For each city, the top 50 most discovered songs are collected every day via the popular mobile application Shazam (Dataset in Methods; see Comparison with other data sources in Methods for comparisons with another music platform and global survey data on cultural values). **(b)** Music discovery similarity among countries within each world region over time (Discovery similarity in Methods). The dashed line indicates the onset of the Russian invasion of Ukraine on February 24, 2022. Values are normalized (z-score) for each region and GAMs fitted for each region over the days. The horizontal dashed line at intercept 0 indicates non-significant changes. The more negative the values, the lower the discovery similarity across countries in a given region (see Supplementary Table 1 for all countries and regions in our data). **(c)** Effect size comparison of average music discovery similarity change comparing pre- and post-invasion periods. **(d,e)** Inferred global network of cultural influence respectively three months before and three months after the invasion based on 79,310 song cascades (Network inference in Methods). Nodes represent cities colored by the world regions, while edges represent directional pathways of diffusion. The post-Soviet region is highlighted in a circle and zoomed in. Interactive visualization of the song's diffusion trajectories is available at https://musicdiscover.net. All values and network inference were derived from 1,000 bootstraps. Shaded areas and error bars correspond to 95% CI (Statistical analysis in Methods).

Asymmetric cultural responses to the war

To gain a deeper understanding of the observed cultural shifts in the post-Soviet region, we studied the content of the music by the language used in the songs, the themes and messages conveyed through the lyrics, and the acoustic characteristics of the music.

The rise of patriotic, local music in Ukraine and the decline of Russian music

We analyzed the proportion of songs discovered in different languages over time (Fig. 2a; Sung language in Methods). In Ukraine, local songs (sung in Ukrainian) were very uncommon prior to the invasion, but rapidly increased after the invasion from 1.84% [1.74, 1.95] to 27.26% [26.92, 27.60] ($d = 4.06$ [3.93, 4.19], $p < 0.001$; see Supplementary Table 2 for top 10 Ukrainian songs post-invasion). In contrast, songs with Russian lyrics discovered in Ukraine decreased from 48.02% [47.67, 48.39] to 26.00% [25.66, 26.33] after the invasion ($d = -3.10$ [-3.23, -2.96], $p < 0.001$). These results reflect a marked rise in expressions of nationalism and patriotism as manifested through increased interest in native language songs.

While we expected to see a similar trend towards local songs in Russia, the observed pattern was the opposite: the proportion of local music (sung in Russian) moderately moderately decreased from 51.42% [51.17, 51.64] to 44.27% [44.01, 44.49] after the invasion ($d = -1.29$ [-1.37, -1.22], $p < 0.001$), with even a small uptick in Ukrainian songs immediately after the invasion. This decline was progressive, reaching a low of 37.20% [34.00, 41.03] in May, three months after the invasion. This may reflect either disengagement or negative sentiment towards the war among the Russian public[13,18,35].

In Belarus, despite its political alliances with Russia, there was a significant decrease in Russian music, from 50.48% [49.80, 51.12] to 39.04% [38.34, 39.67] ($d = -1.74$ [-1.94, -1.56], $p < 0.001$). Interestingly, we see a small but significant ($p < 0.001$) surge in Ukrainian songs in Belarus that were directly associated with themes of war, including anti-Russian sentiments (see Supplementary Table 3 for all 15 Ukrainian songs adopted in Belarus post-invasion).

In Kazakhstan, we observed the least amount of change. Russian music declined slightly from 33.58% [33.26, 33.93] to 28.04% [27.71, 28.38] after the invasion ($d = -1.44$ [-1.61, -1.30], $p < 0.001$), and there was no significant change in local music (sung in Kazakh), suggesting a smaller impact of the Russian invasion on this population.

We tested the stability of these findings over a longer period of two years, from November 2022 to December 2023 (Supplementary Fig. 4; Trend validation in Methods). We found that the elevated discovery of Ukrainian music persisted, and consistently remained above 11.24% [9.55, 12.54], while Russian music remained below 38.82% [36.69, 41.63] and never reverted back to their pre-invasion levels. In contrast, Russian music in all other countries returned to their pre-invasion baselines within a year, implying a shorter-term cultural impact (Supplementary Fig. 4). We also found statistical evidence that seasonal patterns cannot account for these shifts (Supplementary Fig. 5a), and that the observed effects remain large when compared against a general fluctuation of trends that happens over time (Supplementary Fig. 5b; Trend validation in Methods). Moreover, our results cannot be solely attributed to population displacement. This is particularly true in the case of Russia, but also for Ukraine, where forced migration alone cannot explain the emergence of an entirely new trend of patriotic, local music (Fig. 2a).

Ukrainian lyrics reflect topics of war

Focusing on the two countries directly involved in the war, we analyzed the semantic content of songs discovered in Ukraine ($N = 2{,}057$) and Russia ($N = 769$). Using a Large Language Model (LLM) embedding, we extracted feature vectors for each song's lyrics and applied dimensionality reduction using UMAP to visualize semantic relationships between songs (Fig. 2b; Word embedding in Methods). The closer the two songs are in this space, the greater their semantic similarity. We further examined areas of high concentration in the distribution of local (native language) songs in Ukraine and Russia (Comparing distributions in Methods).

In Ukraine, the semantic content of local music changed drastically after the invasion (mean JSD = 0.29 [0.14, 0.45], $p < 0.001$), while in Russia, the changes were significantly smaller (mean JSD = 0.06 [0.03, 0.08], $p < 0.001$; comparison between the two: $p < 0.001$; Fig. 2e; Comparing distributions in Methods). Specifically, post-invasion Ukrainian songs were concentrated around a newly emerged area in the semantic space (Fig. 2b dashed square). Keywords that statistically appeared more frequently were related to topics of war (Fig. 2c; Keywords in Methods), such as expressions of national identity (e.g., “Ukrainian”, “brother”) and direct references to the conflict itself (e.g., “war”, “freedom”, “Muscovite”; see Supplementary Figs. 6a,b for similar results using non-translated versions). In contrast, the semantic content of local music in Russia showed little qualitative difference. The frequency of war-related songs, identified by lyrics containing top five words closely related to “war” in the embedding (War-related songs in Methods), increased in Ukraine over time ($r = 0.71$ [0.63, 0.78], $p < 0.001$), but decreased in Russia (Fig. 2d; $r = -0.64$ [-0.72, -0.55], $p < 0.001$, see Supplementary Fig. 6c for validations with different number of war-related words).

Acoustic changes in music in Ukraine

Analogous to using word embeddings of lyrics, we created an acoustic embedding space through low- and mid-level acoustic features that capture stylistic aspects of the music (Acoustic content in Methods; see Supplementary Fig. 7 for acoustic UMAPs). Mirroring the changes we found in the semantic space above, songs in Ukrainian showed a significantly larger shift in their acoustics (mean JSD = 0.22 [0.06, 0.36], $p < 0.001$) compared to those in Russian (mean JSD = 0.07 [0.04, 0.10], $p < 0.001$; comparison between the two: $p < 0.001$). We next analyzed individual acoustic features by measuring the changes from pre- to post-invasion among Ukrainian and Russian songs. While generally there was not a substantial change in most individual features, we found larger changes for Ukrainian songs after the invasion, characterized by a faster tempo (normalized pre vs. post change = 0.43 [0.20, 0.65], $p < 0.001$) and a decrease in loudness (change = -0.32 [-0.48, -0.14], $p < 0.001$).

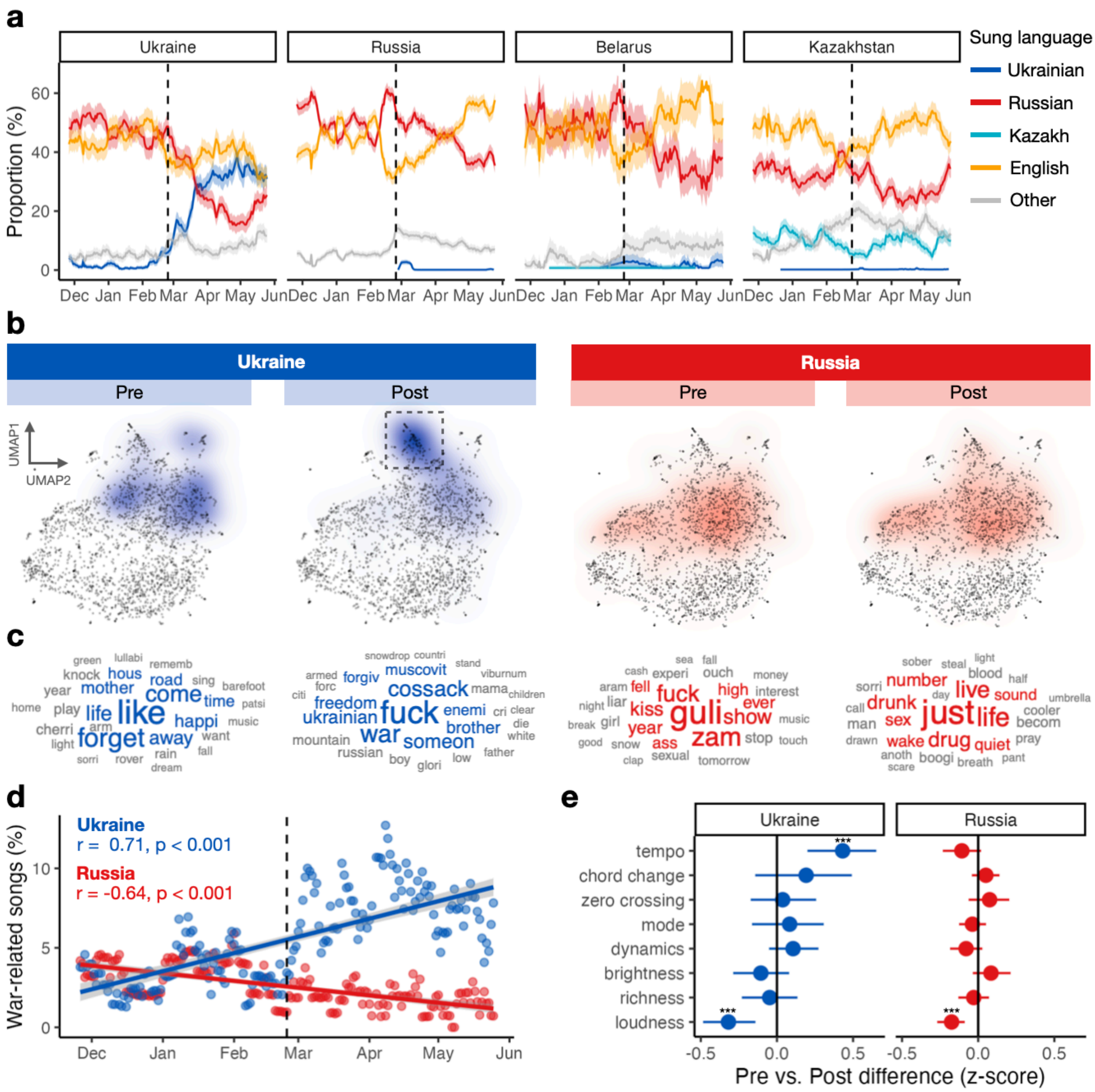

Fig. 2: Asymmetric cultural responses to the war.

(a) Proportion of songs in different languages over time. We automatically detected the language of lyrics of all songs discovered in the post-Soviet countries using machine learning techniques (Sung language in Methods; see Supplementary Figs. 4,5 for longitudinal trends and validations). The dashed line indicates the onset of the invasion. **(b)** UMAP visualization of the lyrics semantic space across all songs discovered in Ukraine (N = 2,057) and Russia (N = 769; Word embedding in Methods). The proximity of songs in this space represents thematic similarity. Kernel density estimation (KDE) is overlaid on the general UMAP to identify areas of high local music concentration. The dashed square box in post-invasion Ukrainian songs shows the emergence of a new theme. **(c)** Word clouds of the top keywords with the top 10 words highlighted in color (Keywords in Methods; see Supplementary Figs. 6a,b for keywords in non-translated versions). **(d)** Frequency of war-related songs over time, defined by song lyrics containing words related to the word "war" (War-related song in Methods; see Supplementary Figs. 6c for validations). **(e)** Acoustic feature analysis comparing the difference between pre- and post-invasion songs in Ukrainian and Russian using normalized values. *** indicate significance at $p = 0.001$. All values were derived from 1,000 bootstraps. Shaded areas and error bars correspond to 95% CI (Statistical analysis in Methods). Interactive visualizations can be found at https://musicdiscover.net.

Factors contributing to cultural change

Our spatially and temporally rich city-level data allows us to investigate nuances of within-country variations (Within-country analysis in Methods). We analyzed these micro-variations, combined with demographic and socio-cultural data, to investigate potential factors contributing to the observed cultural shifts.

Variations in socio-cultural values predict changes in local music discovery

In both Ukraine and Russia, the spatial distribution shifts in local music discovery post-invasion were related to pre-existing socio-cultural values, measured using recent 2017-2020 survey data from the World Value Survey (WVS) (Fig. 3a,b; World Values Survey in Methods). We found that the first three PCA components explained 20.69% of the variance in the survey responses of Ukraine and Russia. One of these three components, related to people who believe in religion and trust in international institutions (e.g., the EU, NATO; see Supplementary Table 5 for description of components), was associated with regional variation in both countries. City populations who were more religious and trusted institutions were more likely to show an increase in local music in Ukraine (Spearman rho = 0.32 [0.16, 0.46], $p < 0.001$). However, in Russia, these same socio-cultural characteristics were associated with a larger decrease in local music (rho = 0.35 [0.22, 0.47], $p < 0.001$; see Supplementary Fig. 8 for correlations with other components).

The variations within each country could also be explained by the underlying demographics. In Russia, the decline in local Russian music discovery was significantly larger in ethnic minority areas ($p = 0.02$; Census analysis in Methods). In the southwest Tartarstan region, cities with a substantial Turkic population such as Kazan (31.53% Bashkr) and Ufa (53.26% Tatars) respectively underwent a decline of -11.70% [-14.05, -9.24] and -10.82% [-13.05, -8.47] after the invasion. Comparable amounts of decline were also observed in cities from the North Caucasus region, where diverse ethnic minority group mixes, such as Stavropol (-11.71% [-14.07, -9.34]) and Makhachkala (-11.10% [-13.59, -8.59]). The ethnicities of the

North Caucasus (now included in several Russian republics and Krais) have a long history of independence movements and resistance against Russian authority[36]. A similar result was observed in Ukraine, where regional variation was significantly related to differences in demographics, such as language (Spearman rho = 0.72 [0.41, 0.88], $p < 0.001$; Supplementary Fig. 9). Namely, Ukrainian cities with larger Russian-speaking populations exhibited smaller changes. These associations suggest that latent variations within these countries have been brought to the surface by the war, and that collective engagement with culture is able to capture such nuances.

The contribution of Russian occupation and population migration

We could further examine the impact of migration by contrasting music discovery patterns among the Ukrainian cities: those expected to experience minimal war-related population movement against those that were battle zones during the study period (i.e., three months preceding and following the invasion). As anticipated, cities primarily speaking Ukrainian (e.g., Kiev, Lviv) exhibited the most pronounced increase in local music (Fig. 3c; pre vs. post change = 30.94% [30.49, 31.36], d = 2.83 [2.77, 2.89], $p < 0.001$). In contrast, a much smaller change was observed in Russian majority speaking cities, which are also cities that have been annexed by Russia in 2014 — namely Donetsk, Luhansk, Kerch, and Sevastopol (change = 4.30 [3.94, 4.66], d = 1.00 [0.93, 1.07], $p < 0.001$).

An interesting exception is Mariupol (Fig. 3c dotted blue line), which is a Russian majority speaking city that has been a battle zone during the study period[8]. The rise and fall of local (Ukrainian) music aligns with the course of historical events. During the initial state of the invasion, Mariupol experienced an increase from 15.29% [2.78, 34.37] in March to 24.24% [8.11, 44.12] in April. This trend gradually decreased as the fighting intensified near the city towards the end of April, further diminishing upon the city's full occupation in May (9.32% [2.63, 25.81]), converging to the levels of previously annexed cities. Such a trend is potentially caused by forced migration or cultural oppression, and likely a combination of both, which might have occurred earlier than our data period in the cities that experienced battle since 2014 (Donetsk and Luhansk)[37,38].

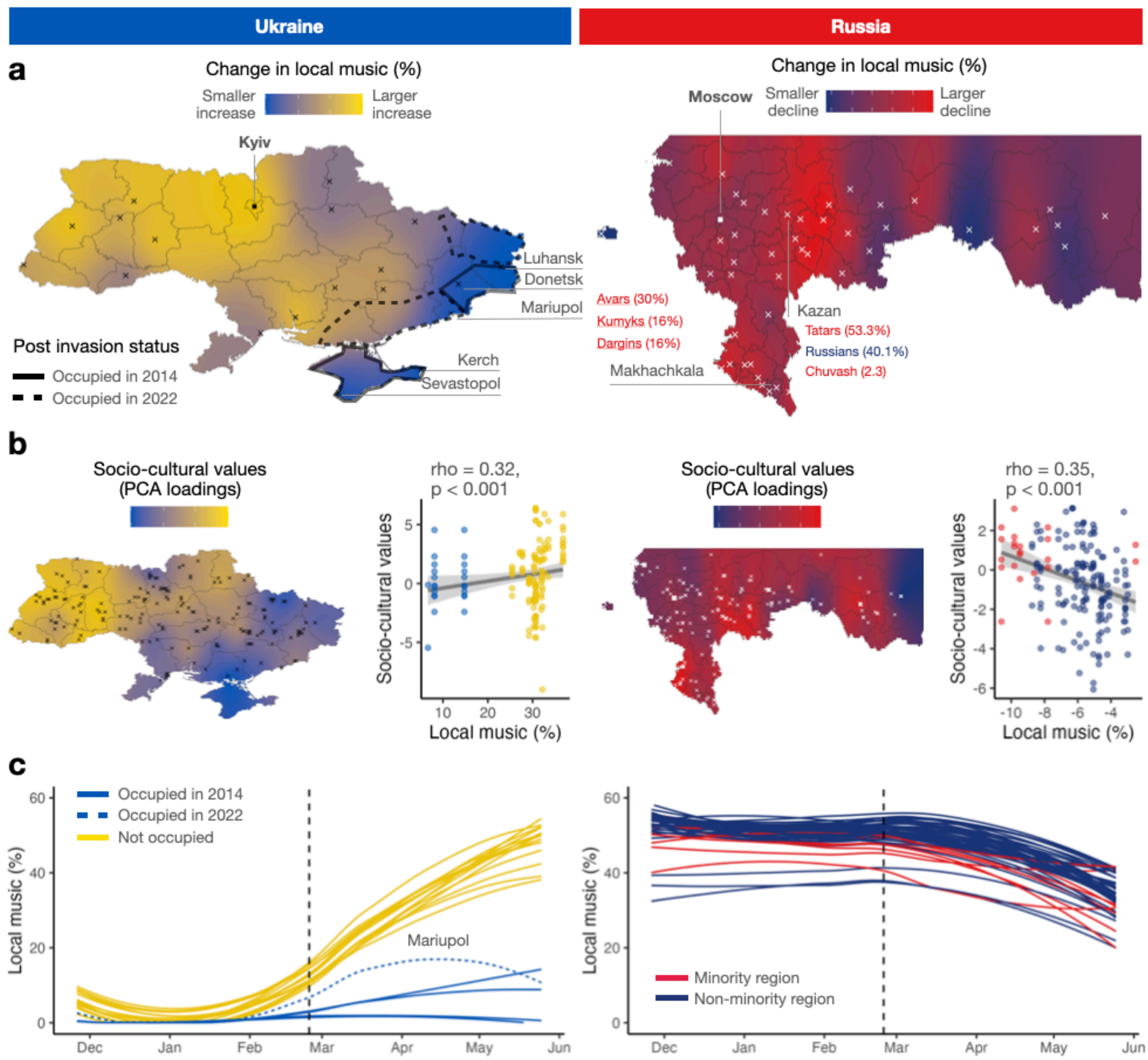

Fig. 3: Subnational trends reveal factors contributing to cultural change.

(a) City-level spatial variations in the proportion of local music within Ukraine and Russia visualized using kernel smoothing over the city locations (City trends in Methods). In Ukraine, higher values (yellow) indicate a larger increase in local music, while in Russia, higher values (red) indicate a larger decline. Occupation status in Ukraine is drawn on the map, while example regions with ethnic minority populations are labelled with census proportion in Russia (Census analysis in Methods). **(b)** Comparison of local music proportion with socio-cultural values using the World Values Survey data (World Values Survey in Methods). PCA of survey responses indicated a three-component solution, explaining 20.69% of the variability (see Supplementary Table 5 for top 10 loadings per component; see Supplementary Fig. 8 for correlations with all components). Results were also replicated using census data (Census analysis in Methods; Supplementary Fig. 9). **(c)** City-level temporal trends of local music proportion in Ukraine and Russia. The dashed vertical line indicates the onset of the invasion. The Ukrainian cities that have previously been annexed (i.e., former Crimea region) or occupied during the war (Mariupol, dotted line) by Russia are coloured in blue. The Russian cities with minority ethnic populations (less than 50% ethnic Russians) are coloured in red. All values were derived from 1,000 bootstraps. Shaded areas and error bars correspond to 95% CI (Statistical analysis in Methods).

We also saw clear traces of the migration process that is in line with Europe's absorption of a substantial immigrant population[9]. The results of the music diffusion analysis (Network analysis in Methods) revealed a significant increase in the formation of new network edges between Ukraine and Europe after the invasion (Mean number of new edges per city = 4.40 [3.80, 5.00]), with only a small change in Russia (M = 1.40 [1.19, 1.67]). Importantly, these new connections were unidirectional, mostly from Ukraine to Europe (Supplementary Fig. 10a). Moreover, the largest number of European cities influenced by Ukrainian music after the invasion were in Poland (Supplementary Fig. 10b), the country that hosted the largest number of Ukrainian refugees[9]. These songs were directly related to themes of war (see Supplementary Table 4 for top 10 Ukrainian songs adopted in Poland post-invasion), suggesting that a large portion of migrants kept discovering their ethnic music while in exile.

Discussion

We investigated worldwide cultural shifts in real-time during major social disruption, including 17.8 million music discoveries, to identify global patterns of societal changes that started months prior to the 2022 Russian invasion of Ukraine. Results revealed cascades of societal disintegration that escalated during the invasion. Our findings identify candidate mechanisms that can potentially explain the observed cultural dynamics. Below we summarize the evidence for and against those mechanisms.

First, several major transitions in music discoveries might have been driven by changes in public sentiment. In Ukraine, the rise of local and patriotic music likely reflects a stronger expression of socio-cultural sentiments such as nationalism and patriotism (Figs. 2a-d). This finding is consistent with previous research on human social behavior during external threats such as war[39–45], and extends other studies showing that war increases adherence to local cultural practices[2,46] and collective action[47,48]. In Russia, local consumption shifted in the opposite direction, with a decrease in the discovery of local, war-related songs. This might reflect the influence of governmental sanctions and control on media[20,49], a negative sentiment towards the war among the Russian public[13,18], or simply a lack of interest[35].

Importantly, music discoveries also captured undercurrents and resistance. For example, in Belarus, engagement with pro-Ukrainian songs increased soon after the invasion, manifesting values against the nation's political alliance with Russia[50,51].

Second, we showed that geographical variation in music discovery patterns is related to predispositions in the populations, such as language and cultural values. After the invasion, cities within Ukraine and Russia displayed distinctive discovery patterns that resonated with pre-existing socio-cultural values (Figs. 3a,b). In Russia, this alignment could also be attributed to the distribution of ethnic minority groups, while in Ukraine, it could be explained by language use (Supplementary Fig. 9). These results extend previous understanding of the mechanisms behind subnational cultural variation[52–55] by demonstrating a direct link with abrupt changes in the environment. Furthermore, these findings complement the extensive humanities research documenting the manifestations of war in human culture — film, music, and art[56–60] — by providing empirical evidence based on large-scale analysis of collective human behavior during wartime.

Finally, the 2022 Russian invasion caused a large-scale refugee crisis, forcing a displacement of millions of people that reshaped the demographics of cities and put others under an occupation regime[8,9]. We found evidence for music discovery patterns that were affected by migration and occupation. Most notably in Mariupol, where discovery patterns closely mirrored the trajectory of invasion (Fig. 3c). We also found a significant increase in discoveries of Ukrainian music in Europe soon after the invasion that was specific to cities with large migrant populations, possibly reflecting the effects of mass migration (Supplementary Fig. 10).

Music discovery vs. social media

Previous social media studies have shown how digital traces can inform real-world events such as natural disasters[61–68], pathogen outbreaks[69–71], and political movements[72–74]. Recently, researchers have used Twitter activity (now X) to study the impact of the Russian invasion on public sentiment and opinion[11–18]. For example, Racek et al.[15] found shifts from Russian to the Ukrainian language among Ukrainian users even before the onset of the 2022 invasion. This is consistent with our findings of early decrease in country-level similarity among the post-Soviet countries (Fig. 1b). These studies have revealed the potential of social media activities for assessing disaster damage and capturing large-scale behavioral changes. Our study adds to these by going beyond differences at the national aggregate level and expands the capacity to situate the war's impact at a more granular scale within a global context by probing culture directly.

Importantly, Shazam discoveries, necessitating active engagement with music played in open spaces, act as unique cultural signifier. Unlike social media posts, which are public and may cause individuals to refrain from expressing their true opinions[75] (particularly in regimes that disregard free speech), engagement with music can encapsulate authentic and shared cultural experiences. Music is closely tied with group identity[76] and social bonding[6], emotion[77], memory[78], and broader public sentiments associated with external events[4,27], making it a powerful marker for societal change. This allows us to directly and continuously monitor shifts in public sentiments and collective preferences.

Limitations and future directions

Our data are limited to Shazam users, which may not fully represent the overall population. As of 2022, Shazam had achieved a global monthly user base of 225 million and 20 million daily discoveries[79]. However, people who do not use this mobile application are missing from the data. This imposes a selection bias in favor of WEIRD (Western, Educated, Industrial, Rich, Democracies) populations[80]. Specifically, our data does not cover some geographical locations in the global south and only includes post-Soviet countries available from Shazam. Shazam and other application users also may not be representative of the general demographics in age and gender[81]. Future research can address this gap by complementing our data with other rich sources of music and cultural products available more globally, such as YouTube[82] and Google Trends[83].

Behavior recorded by commercial data systems including Shazam, might be affected by endogenous factors other than the behavior of its users, such as algorithms and company goals, which may be enough to influence macro-level trends in music consumption[84,85]. To evaluate the quality of data published in Shazam, we compared the data to popular music consumed on Spotify and found a moderate amount of overlap (Music preferences in Methods). We also found a strong relationship ($r = 0.65$ [0.65, 0.66], $p < 0.001$) between pairwise city-level music similarity and socio-cultural values measured using self-report survey data (Socio-cultural values in Methods), suggesting that collective music engagement captured by Shazam reflect real-world similarities in cultural values and interests. For a more direct assessment, collaborations with industry would provide an exciting avenue to address these potential biases[81,86].

Finally, we infer statistically reliable changes in relation to the onset of the invasion, but we cannot experimentally test for causal links[87]. However, we tested the robustness of our results to seasonal patterns (Supplementary Fig. 5a) and against general variations in trends (Supplementary Fig. 5b). We also assessed the stability of the trend over a longer period of two years (Supplementary Fig. 4), with cultural shifts in Ukraine consistently showing the greatest strength and stability over time. Causal manipulation can be explored more directly with recent breakthroughs in computational and experimental techniques, which allow the simulation of complex cultural dynamics with human participants in highly controlled settings, such as artificial social networks[88,89] and cultural transmission experiments[24,90,91].

More broadly, our work has implications in two complementary directions that contribute to the understanding of human societies and cultures. First, our work demonstrates how music can be used to characterize, monitor, and even predict societal changes, thereby contributing to the tools available to policy makers to formulate strategies that promote unity and resilience in the face of adversities. Second, our work provides insights into interactions between culture and society that would be otherwise hidden or very hard to disentangle. The shock-wave of the invasion reveals the pathways through which extremely disruptive events imprint the daily shared experiences of culture, contributing to our understanding of the evolution of human culture.

Methods

Dataset

Global Music Discovery dataset

People are constantly exposed to music in everyday environments, from cars and homes to restaurants, bars, and shopping malls[26,92]. This exposure often sparks curiosity, for example, in discovering the song's title and the artist who created it. Shazam (https://www.shazam.com) is a popular mobile application that allows users to search and identify music by recording a short audio sample (~ 5 seconds) using the device's microphone. It uses an audio fingerprint to find a match in a database of millions of songs[33]. If it finds a match, the track's title and artist are sent to the user, who can save the track to their personal library, share it with friends, or stream it on other audio platforms like Apple Music. As of 2022, Shazam had achieved over 70 billion song identifications, with a global monthly user base of 225 million and 20 million daily Shazams[79].

Shazam's search feature captures behavioral data that reflects how people discover music in real-world environments (e.g., cars, restaurants, bars) and social contexts (e.g., commuting, working, socializing). Although the reasons behind music discovery in the app can be diverse[93], at a minimum, they represent a mixture of personal music interest, reflecting their preference (i.e., songs they like) and curiosity (i.e., songs they are unfamiliar with but want to know more about or share with others; see Music preferences in Methods for comparison with Spotify chart).

We implemented a daily web crawler to collect the top 50 most-searched-for songs in 1,423 cities across 53 countries, which were all the ones that were available from the Shazam website (Fig. 1a). This crawler gathered data for more than three years. According to Shazam, these charts represent weekly most discovered songs. The chart is updated frequently as our monitoring was able to capture changes happening at the day-to-day granularity. From our longitudinal collection of this data, we sampled a period of six months as the study window — from 26th November 2021 to 25th May 2022. In this time window, there were over 12.8 million music discovery events corresponding to 79,310 unique songs. We also collected two-years longitudinal data (from 26th November 2021 to 15th December 2023). Longitudinal analysis reported in Supplementary Fig. 4 includes a summary of 66.5 million events and 273,988 unique songs. We call this the Global Music Discovery dataset. The dataset only uses aggregate data of the most popular songs identified in Shazam both at the city and country level (Data and code availability). None of the queries used in the data can be linked to any particular individual or reveal private information. We created a web page with interactive plots for analysis and data exploration and visualization (https://musicdiscover.net).

World regions

We categorized the world into seven regions based on the World Bank analytical grouping[94]. This classification includes economies at all income levels and may differ from common geographic usage or regions defined by other organizations. Given that our study focuses on understanding cultural shifts in the post-Soviet countries, we made a separate category for the post-Soviet region, which includes all countries from the former Soviet Union available in our dataset, namely, Ukraine, Russia, Belarus, and Kazakhstan. We refer to the "Europe & Central Asia" region only as "Europe", as our dataset did not include any Central Asian countries. The categories of world regions defined in the study are visible as a world map in Fig. 1a. Supplementary Table 1 outlines the classification of all 53 countries.

Discovery similarity

To examine temporal trends in the similarity of song discoveries within each world region (i.e., their shared repertoire), we calculated the daily proportion of song overlap consumed among countries per region. This was measured using the Jaccard similarity coefficient $J(A,B)$, defined as the size of the intersection of two song sets in countries A and B, divided by the size of their union, bootstrapped across the songs for each day (Statistical analysis in Methods). Regions that consisted of a single country — South Asia and Sub-Saharan Africa — were excluded from the analyses as between-country comparisons could not be made. Similar measures of shared cultural consumption have been found to reflect cultural similarities that change along the economic, social, and geopolitical dimensions across countries[82,83]. For cross-regional comparisons, the values were normalized using z-scores. Cases where the values were above or below two standard deviations were treated as outliers and excluded. To visualize the trends, a Generalized Additive Model (GAM)[95] was fitted to each bootstrap and then averaged (Fig. 1b), with extent of positive or negative trends computed using the coefficients over the time axis. The general magnitude of change between pre- and post-invasion was measured using bootstrapped Cohen's d effect size estimates (Fig. 1c; Statistical analysis in Methods).

Network analysis

Network inference

Using the Global Music Discovery dataset, we compiled the diffusion cascades of all unique songs (N = 79,310). A song cascade describes the trajectory of a song as it becomes popular across cities over time (see https://musicdiscover.net for interactive visualization of cascades for selection of songs). To infer likely directional pathways of diffusion based on multiple song cascades, we used the NETINF[34] algorithm, a generative probabilistic network model that has been extensively used to reconstruct the underlying diffusion networks of online media, such as social media, blogs, and news articles. Given only the times when cities adopt new songs, the algorithm is able to reconstruct the connectivity of the underlying network by maximizing the likelihood of the observed cascades under the probabilistic model. Specifically, the model infers a directed edge (*A*, *B*) in the network if city *B* tends to adopt new song trends soon after city *A* across multiple cascades.

To construct the final network, we ran the model 1,000 times, bootstrapping a balanced number of 100 unique songs across all cities each time (Statistical analysis in Methods). Split-half correlation suggested that 100 bootstrap datasets are sufficient to obtain a reliable estimate of the network (see Supplementary Fig. 11 for network reliability analysis). Next, we aggregated all bootstrapped networks into a single weighted network by summing all unique edges. We used the frequency of edges between two nodes as a measure of edge strength (or weights), which reflects the degree of shared musical interests (i.e., similar music discovery trends). Edge strength ranges from 0 (edge was not inferred in any of the bootstrap datasets) to 1,000 (edge was inferred for every bootstrap datasets). When visualizing the resulting network (Network visualization in Methods), we reduced the density of the inferred networks by removing weak edges that occurred less than 5% of the time. We found this threshold to provide a good tradeoff between removing noisy edges with little structural importance, at the same time, maintaining meaningful structures of the networks both globally and locally.

Network validation

To test the robustness of the NETINF algorithm, we repeated the network analysis in the post-Soviet region (Figs. 1d,e insets) using a simpler method based on the co-occurrences of songs between cities. This is analogous to the approach of measuring discovery similarity (Discovery similarity in Methods), where we computed the overlap of songs between all pairs of 100 post-Soviet cities in the Global Music Discovery dataset. We then compared the weights of the edges in the networks obtained using this method and the NETINF algorithm, which indicated a significant degree of overlap between the adjacency matrices for both pre- ($r = 0.49$ [0.48, 0.51], $p < 0.001$) and post-invasion ($r = 0.56$ [0.55, 0.58], $p < 0.001$) networks, validating the robustness of the NETINF algorithm. We chose to use the network inference approach in the main study as it is able to account for temporal trends of songs and infer directional pathways of influence. Additionally, we visualized the co-occurrence network for comparison (Supplementary Fig. 3). We reduced the density of the network by applying a backbone algorithm[96] to the city-by-city matrix, obtaining only the edges that were statistically significant using the disparity filter in the *backbone*[97] package in R. We balanced the resulting number of edges in the pre- (N edges = 1,014) and post-invasion (N edges = 966) networks by adjusting the alpha level to 0.285 and 0.230 respectively.

Network similarity and change

We compared the similarity between pre- and post-invasion networks at a global scale by computing bootstrapped split-half Pearson correlation between the city-by-city pairwise matrices obtained through the NETINF algorithm (Network inference in Methods; see Supplementary Fig. 1 for heatmaps). We computed the amount of change in the networks by measuring the percentage change in the number of edges in the pre- (N_{pre}) and post-invasion (N_{post}) networks, written as:

$$\text{Percentage of change} = \frac{(N_{\text{post}} - N_{\text{pre}})}{N_{\text{pre}}} \times 100 \quad (1)$$

This procedure was performed separately for each NETINF inference bootstrap datasets and aggregated to provide the mean and confidence estimates (Statistical analysis in Methods). Using the formula, we examined the changes within each world region (Supplementary Fig. 2).

Ukraine, Russia, and Europe

For each city in Ukraine and Russia, we computed the number of new edges formed with cities in Europe, including both incoming edges (from Europe) and outgoing edges (to Europe; Supplementary Fig. 10a). To explore which cities in Europe developed new edges with the post-Soviet region, we created a geographical map visualization (Supplementary Fig. 10b) indicating any city in Europe with at least one new edge formed in the post-invasion network (i.e., edge that did not exist in the pre-invasion network).

Network visualization

We performed several steps to ensure an alignment of layouts of the pre- and post-invasion networks for visual comparisons. First, we created two city-by-city matrices to represent the inferred networks of pre- and post-invasion. The matrices ($A_{i,j}$) contained all possible pairwise comparisons across the 1,423 cities, using the inferred edge strength (Network inference in Methods) ranging from 0 (edge is absent) to 1,000 (maximum possible edge strength). Second, we joined the original matrices with their transposed versions to form a new joint matrix, written as:

$$C = \begin{bmatrix} A & A' \\ B & B' \end{bmatrix} \qquad (2)$$

where A and B are the original matrices, and A' and B' are their matrix transpositions ($A'_{i,j} = A_{j,i}$). The transposition step ensures that both incoming and outgoing edges are taken into equal account. Finally, to get a normalized similarity matrix, we computed the correlations, where C is n x p matrix, then the correlation $D[i,j]$ is calculated as:

$$\frac{cov(C[:,i], C[:,j])}{std(C[:,i]) \times std(C[:,j])} \qquad (3)$$

The last two steps (equations 2 and 3) ensure that the pre- and post-invasion matrices are distributed within the same shared visualization space.

Our method offers a considerable advantage over previous visualization methods that perform dimensionality reduction independently, and then attempt to align networks *a posteriori*[98,99]. We used Gephi (https://gephi.org) for the final visualization of the networks, an open-source visualization software for graphs and networks. The layout was determined using the *Yifan Hu Proportional* method[100] (optimal distance = 120, relative strength = 0.20, convergence ratio = 0.0001). We first obtained the joint visualization using both pre- and post-networks and then separated them to display them as independent subplots (Fig. 1d,e).

Music content analysis

Sung language

We determined the language of songs' lyrics using *FastText*, a pre-trained word embedding machine learning model capable of identifying 176 languages[101]. We excluded 37.50% of songs which contained no lyrics. While this is a relatively large proportion, the number of missing lyrics across the post-Soviet countries were similar, ranging between 26.06% to

38.24%. We further excluded 8.98% of songs that resulted in a low confidence score in language identification (below 0.70 with full range from 0 to 1). A song was considered “local music” if the language of its lyrics matched the country of discovery (e.g., a song in the Ukrainian language discovered in Ukraine). We calculated the proportion of songs in the most frequent languages across the post-Soviet countries (Ukrainian, Russian, Kazakh, and English) by bootstrapping songs across the days, with effect sizes of change computed comparing pre- and post-invasion periods (Fig. 2a; Statistical analysis in Methods). Non-English lyrics were translated into English using DeepL (https://www.deepl.com).

Trend validation

We tested the robustness of our results in several control analyses (Fig. 2a; Sung language in Methods). First, we tested the stability of our results over a longer time window of two years, from November 2021 to December 2023 (Supplementary Fig. 4). Specifically, we tested the extent to which the trends of songs’ language observed for six months in our sudy window persisted (Fig. 2a). For each country, we computed the first day in which the proportion of Ukrainian or Russian songs returned to their pre-invasion baselines (defined as the mean proportion of the entire pre-invasion period). The results revealed that the cultural shifts observed in Ukraine (increase in local music and decrease in Russian music) persisted over the next year: Ukrainian music consistently remained above 11.24% [9.55, 12.54], while Russian music did not exceed 38.82% [36.69, 41.63]. In contrast, the cultural shifts observed in Russia, Kazakhstan, and Belarus (decrease in Russian music) returned to their baseline levels within a year (see Supplementary Fig. 4 for long-term trends). Specifically, it took 208 [207, 211] days after the invasion for Russia, 117 [41, 217] days for Belarus, and 89 [85, 116] days for Kazakhstan.

Second, we tested for potential seasonal effects, as particular months in the year (e.g., holiday seasons, christmas) can link to different consumption patterns[27,102]. We compared the trends in our study with the same months in the following year by computing Pearson correlations between the two trends (Supplementary Fig. 5a). Across the four post-Soviet countries, we found no evidence showing the same trends in the same months of the following year (correlations were either small and non-significant, $p > 0.05$, or negatively correlated), ruling out the possibility that our results are explained by seasonal patterns. Finally, we examined the relative magnitude of the effects we observed in the study period against the fluctuation in trends that happens over time (Supplementary Fig. 5b). Excluding the study period months, we randomly sampled the same six months period window across the entire longitudinal data using 1,000 bootstraps (Statistical analysis in Methods). We split each of these samples in half and compared the changes by the effect size, resulting in a distribution of potential trends. We then examined how our observed effect falls in this distribution. Our results showed that the trends in Ukraine and Belarus were significantly above chance ($ps < 0.001$), falling outside the expected values accounted for by random fluctuations. The results observed in Russia ($p = 0.44$) and Kazakhstan ($p = 0.10$) were in the expected direction to the norm, but not statistically significant.

Word embedding

We used pre-trained word embeddings available from Open AI (www.openai.com, model *text-embedding-ada-002*, data collected in December 2023) to extract semantic vectors of the songs based on lyrics. This embedding forms the bases for the Large Language Models (LLMs) developed by the company and used in their application GPT. For each song that was discovered in Ukraine and Russia where lyrics are available ($N = 2,826$), we used the API query to extract the word embedding feature vectors of the lyrics, consisting of 1,536 dimensions.

Keywords

To identify the keywords that stem from Ukrainian and Russian songs pre- and post-invasion, we computed the log-odd ratio approach described by Monroe et al[103]. This approach is similar to term frequency–inverse document frequency (TF-IDF), a widely used approach in Natural Language Processing to identify important words across documents[104]. Each word was assigned a zeta-score that indicates the importance of the word in the group (i.e., pre- versus post-invasion songs). We then cleaned and processed (e.g., lemmatization) the words in the lyrics with custom stopwords to remove interjections such as “ooh” and “yeah” (based on two author agreements). Next, we extracted the 30 top zeta ranked keywords from the Ukrainian and Russian lyric songs, separately for pre- and post-invasion as word cloud visualizations using the *ggwordcloud*[104] package in R (see Supplementary Figs. 6a,b for word clouds in the original languages and back-translated versions).

War-related songs

We used a data-driven approach to identify war-related words based on the same word embedding extraction method described above (Word embedding in Methods). We applied a tokenized dictionary of all words (instead of entire lyrics) across songs discovered in both Ukraine and Russia to identify war-related songs. Using the seed word "war", we computed the cosine similarity across the embedding vectors of all tokenized words to find the closest neighboring words. This approach is analogous to previous studies relying on language models to assess semantic similarity[105,106]. Songs were then classified as war-related if their lyrics contained any of the top five war-related words — "war", "weapon", "bullfight", "combat", and "armed". We then calculated the daily proportion of songs that contained any one of these words in Ukraine and Russia, bootstrapping over songs per day (Statistical analysis in Methods). We found similar results when varying the number of war-related words, including only the inclusion of the word "war", the top three and the top ten neighboring words (Supplementary Fig. 6c).

Acoustic features

We used the Essentia library[107] (version *2.1-beta6-dev*) to extract low- and mid-level acoustic features of the songs discovered in Ukraine and Russia by using all available preview audio links for download and audio extraction (N = 2,222). Following standard practices in the music information retrieval literature[23], we included acoustic features that captured different aspects of music, ranging from timbre and rhythm to musical chords. Specifically, we computed the RMS loudness, dynamic complexity, spectral complexity, spectral centroid, spectral energy, zero-crossing-rate, beats per minute (bpm), chord change rate, mode (major or minor), and 12 bins of MFCC values. We used the low- and mid-level features as acoustic vectors for distribution comparison and visualization (see Supplementary Fig. 7 for UMAP). We further compared each feature independently for pre- and post-invasion local songs in Ukrainian and Russian by computing the change (post mean - pre mean; Fig. 2e). All values were derived from 1,000 bootstraps across the songs (Statistical analysis in Methods).

Comparing distributions

We used UMAP for reducing the high dimensional vectors of semantic and acoustic features, using the *uwot*[108] package in R. Cosine similarity was used as a measure of distance, taking ten neighbors, which gave a good balance between the local and global structure. The proximity between two songs in the semantic space corresponds to the extent of shared semantic content (e.g., songs that talk about love or friendship), while proximity in acoustic space corresponds to similar musical styles as measured by their acoustic characteristics (e.g., songs that have similar timbre, rhythm, or music genre).

To identify high density areas of local music, we overlaid Kernel Density Estimations (KDE) on the UMAPs of Ukraine and Russia for pre- and post-invasion songs separately. We used the *MASS*[109] package in R to compute each density map with a grid size of 512 by 512. We then computed kernel smoothing with a Gaussian kernel with width selected by their best-practice heuristic with default parameters implemented in the package.

To measure differences between distributions of songs (*P* and *Q*) in the semantic and acoustic spaces between pre- and post-invasion songs, we computed the Jensen–Shannon Divergence (JSD) using the *philentropy*[110] package in R, written as:

$$JSD(P,Q) = \frac{1}{2}D(P,M) + \frac{1}{2}D(Q,M) \quad (4)$$

where *M* is defined as:

$$M = \frac{1}{2}(P+Q) \quad (5)$$

and *D(P,Q)* is defined as:

$$D(P,Q) = \int p(x)\log_2\left(\frac{p(x)}{q(x)}\right)dx \quad (6)$$

Note that the JSD is symmetric and results in a value between 0 and 1. When the two distributions are identical, the JSD is 0, while 1 when they are completely non-overlapping. Since JSD does not have a value below 0, we created a random baseline for reference by shuffling the pre- and post-labels. We then computed bootstrap estimates over the songs by taking the difference between true JSD and the random baseline as the estimate, where values near 0 indicate support for the null hypothesis (Statistical analysis in Methods).

Within-country analysis

City trends

We used our city-level data to study subnational variations within Ukraine and Russia, using language of the lyrics as a proxy for local music (Sung language in Methods).

To examine changes at the geographical level (Fig. 3a), we created a geographical raster map by using a kernel smoothing technique to interpolate geospatial data across a predefined grid of city locations. This method estimates values across the entire grid based on the spatial distribution of the observed data points. The geographical map was represented as a grid of cells, each defined by longitude and latitude coordinates. For visualization, we divided the cities into four quantiles based on their proportion of local music change from pre- to post-invasion. The quantile splits accounted for the skewness in the distribution of data points and ensured consistent mapping across all our geographical visualizations. Kernel smoothing was applied as follows:

$$G_D(x) = \exp\left(-\frac{x}{D}\right) \quad (7)$$

where *x* represents the distance between a grid cell and a data point, *D* is a distance parameter determining the smoothing extent. This function ensured that closer points had a higher influence on the interpolated value at a given grid cell, with the influence decreasing exponentially with distance. The interpolation across the grid was achieved through the following process: (1) for each cell in the grid, distances to all data points were calculated, and corresponding weights were derived using the smoothing function; (2) these weights were then normalized so that the overall weights sum to one; (3) the interpolated value for each cell was obtained by computing the weighted sum of the values of all points, with weights reflecting the spatial relationship between the cell and the points based on the defined smoothing function. The distance parameter *D* was set based on the mean distance between all pairs of data points divided by 10 to obtain sufficient spatial resolution.

To examine temporal trends (Fig. 3c), we calculated the proportion of local music per city within Ukraine and Russia for each day, bootstrapping over the songs and by fitting a GAM over the bootstrapped means (Statistical analysis in Methods).

World Values Survey

To examine the associations between city-level variations in change in local music and pre-existing socio-cultural values within Ukraine and Russia, we used the World Values Survey (WVS) data collected from 2017 to 2022, which covers 64 countries (*Wave 7*)[111]. WVS is a longitudinal global research project that includes more than 300 questions to measure people's social, political, economic, religious, and cultural values.

A total of 1,289 survey responses across 351 unique geolocations were available from Ukraine, and 1,796 responses across 189 geolocations from Russia. After excluding 58 questions that had no responses both in Ukraine and Russia, there were 318 questions remaining. To reduce noise, the geolocations were re-grouped by a single decimal granularity of latitude and longitude geocoordinates. Survey response values corresponding to 0 were treated as missing and were replaced by the mean value of their higher-level geographical boundary (i.e., iso 3166-2 corresponding to municipalities, see https://www.iso.org/standard/72483.html). To account for different units and response types, all questions were standardized with z-scores.

To reduce the dimensionality of the questions into fewer meaningful factors, we performed a Principal Component Analysis (PCA) including all data available in the two countries, using the base function *prcomp* in R. We found that the three first latent dimensions explained 20.69% of the variance (see Supplementary Table 5 for the top 10 loadings and related questions for each dimension). The first dimension (accounting for 7.70%) captured variability in socio-cultural values related to *ethical and moral judgements*, measuring the extent to which individuals are against unethical actions and behaviors (e.g., stealing property, terrorism, violence, domestic abuse). The second dimension (accounting for 6.90%) captured *low institutional trust*, including institutions such as the government, the police, and the justice system. The third dimension (accounting for 6.09%) captured *religiosity and trust in international institutions*, including importance of religion, belief in heaven, and trust in major international institutions (e.g., the European Union, NATO, and the United Nations). Both in Ukraine and Russia, the loadings of PCA 3 (Fig. 3b) were significantly associated with changes in local music discovery post-invasion ($ps < 0.001$). The results using PCA 1 and PCA 2 only revealed a significant correlation with PCA 1 in Ukraine ($p < 0.01$), while the other associates were non-significant (see Supplementary Fig. 8). We used the same smoothing technique described above (City trends in Methods) to visualize the PCA loadings of each city as a raster map.

Census analysis

We replicated our findings of Fig. 3b using census data on ethnic and linguistic proportions in Ukraine, and only ethnic data in Russia due to the lack of available linguistic data (Supplementary Fig. 9). For Ukraine, we used the 2001 Census. This is the first (and the last, making it most recent) national census conducted in Ukraine since it gained independence from the Soviet Union in 1991, carried out by the State Statistics Committee of Ukraine (https://stat.gov.ua). There are many debates surrounding the validity of the 2001 census[112,113], and considering it is two decades old, any interpretation needs to be taken with caution. For Russia, we used the most recent 2021 Census, carried out by the Russian Federal Government (https://eng.rosstat.gov.ru). The results of census analysis were similar for Ukraine but did not reach significance for Russia (see Supplementary Fig. 9 for further statistics).

Comparison with other data sources

Music preferences

To examine the extent to which music discovery data from Shazam aligns with popular music consumption, we compared the top 200 weekly charts of Shazam with the top 200 weekly charts of Spotify (https://spotify.com), one of the largest music streaming services. Given that Spotify does not openly publish city-level charts, we compared data at the country level across the 47 countries that overlap between the two platforms. Among these countries, we gathered data of the same half a year period (June to December 2021) and computed the number of top 200 chart songs of Spotify that were also present in the top discoveries of Shazam. To account for potential minor discrepancies in song title and artist name spellings across platforms, we used fuzzy string matching via the *stringdist*[114] package in R. This process involved creating a single composite string for each song (combining song title and artist name) and comparing these across the two platforms. The matching algorithm generates a score between 0 and 1, with 0 indicating completely different strings and 1 indicating identical strings. We established a threshold of 0.70 to determine whether a match was considered successful, a threshold that has shown to be reliable in matching songs across different sources[115].

Of the 18,090 songs in the entire set of Spotify chart, 7,258 songs were also present on Shazam chart (40.1%). After segregating the songs by country and month, we found that on average 29.2% [26.5, 31.9] of the songs on Spotify were present in Shazam of the same month. This moderate degree of overlap across platforms likely reflects the feedback loop between music listening and discoveries. For example, widely popular songs are more likely to be played in public spaces, leading to more exposure and discovery opportunities by listeners. At the same time, the discrepancies between the two platforms highlight the differences between passive musical preferences (users listening to their favorite songs or curated playlists on Spotify) and active seeking behavior (users wanting to discover new songs using Shazam).

Socio-cultural values

To examine the extent to which music discovery data from Shazam reflects shared cultural interests and values globally, we compared the pairwise music similarity across all countries using the Global Music Discovery dataset, with the pairwise similarity in socio-cultural values derived from the WVS data (World Values Survey in Methods). Music pairwise similarity was calculated using the Jaccard similarity coefficient (Discovery similarity in Methods). Socio-cultural similarity was calculated using the cosine similarity across all the questions on WVS. The locations where the survey was collected were first matched with the Shazam data by finding the minimum haversine distance between the two datasets. We then excluded all surveys that were conducted more than 100 km away from the nearest city included in the Shazam data. This resulted in a match of 508 cities, while the two similarity matrices revealed a strong correlation ($r = 0.63$ [0.63, 0.63], $p < 0.001$). This suggests that cross-cultural similarity in people's musical interests align with similarities in socio-cultural values.

Statistical analysis

Unless stated otherwise, all bootstrap analyses were performed with 1,000 datasets with replications to derive the mean. Confidence estimates were derived from the 2.5% and 97.5% quantiles of the bootstrap means. For statistical test comparing two conditions, we determined statistical significance at alpha level of 0.05 using non-parametric tests. Pearson and Spearman correlations were adjusted for multiple comparisons using Bonferroni method. Pearson correlation is reported throughout, with an exception of analysis on within-country variation (Within-country analysis in Methods) where Spearman correlation was used due to the skewness of the data. Cohen's d was used for effect size estimates with signs to indicate the direction of effect[116]. Data analysis was conducted using R (version *4.4.0)*. All analysis scripts are available for transparency and reproducibility (Data and code availability).

Data and code availability

All analysis scripts describing the working and plottings used for the study are available at https://github.com/harin-git/mus-war. All data is available as part of the OSF repository at https://osf.io/ra38k. We also include a web page with an interactive version of the main figures at https://musicdiscover.net.

References

1. Boyd, R., Richerson, P. J. & Henrich, J. The cultural niche: Why social learning is essential for human adaptation. *PNAS Proc. Natl. Acad. Sci. U. S. Am.* **108**, 10918–10925 (2011).
2. Henrich, J., Bauer, M., Cassar, A., Chytilová, J. & Purzycki, B. G. War increases religiosity. *Nat. Hum. Behav.* **3**, 129–135 (2019).
3. Jackson, J. C., Gelfand, M., De, S. & Fox, A. The loosening of American culture over 200 years is associated with a creativity–order trade-off. *Nat. Hum. Behav.* **3**, 244–250 (2019).
4. Kim, K., Askin, N. & Evans, J. A. Disrupted routines anticipate musical exploration. *Proc. Natl. Acad. Sci.* **121**, e2306549121 (2024).
5. Mehr, S. A. *et al.* Universality and diversity in human song. *Science* **366**, eaax0868 (2019).
6. Savage, P. E. *et al.* Music as a coevolved system for social bonding. *Behav. Brain Sci.* **44**, e59 (2021).
7. Baumard, N., Huillery, E., Hyafil, A. & Safra, L. The cultural evolution of love in literary history. *Nat. Hum. Behav.* **6**, 506–522 (2022).
8. Haque, U. *et al.* The human toll and humanitarian crisis of the Russia-Ukraine war: the first 162 days. *BMJ Glob. Health* **7**, e009550 (2022).
9. UNHCR. Situation Ukraine Refugee Situation. *Opertional Data Portal* https://data.unhcr.org/en/situations/ukraine (2024).
10. Janowski, K. Civilian Deaths In Ukraine War Top 10,000. *United Nations.* https://ukraine.un.org/en/253322-civilian-deaths-ukraine-war-top-10000-un-says (2023)
11. Geissler, D., Bär, D., Pröllochs, N. & Feuerriegel, S. Russian propaganda on social media during the 2022 invasion of Ukraine. *EPJ Data Sci.* **12**, 1–20 (2023).
12. Caprolu, M., Sadighian, A. & Di Pietro, R. Characterizing the 2022- Russo-Ukrainian Conflict Through the Lenses of Aspect-Based Sentiment Analysis: Dataset, Methodology, and Key Findings. In *Proc. Int. IEEE Conf. ICCCN* (2023).
13. Garcia, M. B. & Cunanan-Yabut, A. Public Sentiment and Emotion Analyses of Twitter Data on the 2022 Russian Invasion of Ukraine. in *Proc. Int. Conf. ICITACEE* 242–247 (2022).

14. Xia, Y. *et al.* The Russian invasion of Ukraine selectively depolarized the Finnish NATO discussion on Twitter. *EPJ Data Sci.* **13**, 1 (2024).
15. Racek, D., Davidson, B. I., Thurner, P. W., Zhu, X. X. & Kauermann, G. The Russian war in Ukraine increased Ukrainian language use on social media. *Commun. Psychol.* **2**, 1–14 (2024).
16. Mir, A. A., Rathinam, S., Gul, S. & Bhat, S. A. Exploring the perceived opinion of social media users about the Ukraine–Russia conflict through the naturalistic observation of tweets. *Soc. Netw. Anal. Min.* **13**, 44 (2023).
17. Gulzar, R. *et al.* Analyzing the online public sentiments related to Russia-Ukraine war over Twitter. *Glob. Knowl. Mem. Commun.* (2023).
18. Dean, M. C. & Porter, B. Sentiment Analysis of Russian-Language Social Media Posts Discussing the 2022 Russian Invasion of Ukraine. *Armed Forces Soc.* 0095327X241235987 (2024).
19. Scharbert, J. *et al.* Psychological well-being in Europe after the outbreak of war in Ukraine. *Nat. Commun.* **15**, 1202 (2024).
20. Jawaid, A., Gomolka, M. & Timmer, A. Neuroscience of trauma and the Russian invasion of Ukraine. *Nat. Hum. Behav.* **6**, 748–749 (2022).
21. Patel, S. S. & Erickson, T. B. The new humanitarian crisis in Ukraine: Coping with the public health impact of hybrid warfare, mass migration, and mental health trauma. *Disaster Med. Public Health Prep.* **16**, 2231–2232 (2022).
22. Savage, P. E. *et al.* Sequence alignment of folk song melodies reveals cross-cultural regularities of musical evolution. *Curr. Biol.* **32**, 1395-1402.e8 (2022).
23. Mauch, M., MacCallum, R. M., Levy, M. & Leroi, A. M. The evolution of popular music: USA 1960–2010. *R. Soc. Open Sci.* **2**, 150081 (2015).
24. Ravignani, A., Delgado, T. & Kirby, S. Musical evolution in the lab exhibits rhythmic universals. *Nat. Hum. Behav.* **1**, 1–7 (2016).
25. Savage, P. E., Brown, S., Sakai, E. & Currie, T. E. Statistical universals reveal the structures and functions of human music. *Proc. Natl. Acad. Sci.* **112**, 8987–8992 (2015).
26. Rentfrow, P. J. The role of music in everyday life: Current directions in the social psychology of music. *Soc. Personal. Psychol. Compass* **6**, 402–416 (2012).
27. Park, M., Thom, J., Mennicken, S., Cramer, H. & Macy, M. Global music streaming data reveal diurnal and seasonal patterns of affective preference. *Nat. Hum. Behav.* **3**,

230–236 (2019).

28. Greenberg, D. M. & Rentfrow, P. J. Music and big data: a new frontier. *Curr. Opin. Behav. Sci.* **18**, 50–56 (2017).
29. Way, S. F., Garcia-Gathright, J. & Cramer, H. Local Trends in Global Music Streaming. *Proc. Int. AAAI Conf. Web Soc. Media* **14**, 705–714 (2020).
30. Mok, L., Way, S. F., Maystre, L. & Anderson, A. The Dynamics of Exploration on Spotify. *Proc. Int. AAAI Conf. Web Soc. Media* (2022).
31. Grossmann, I. & Varnum, M. E. W. Social Structure, Infectious Diseases, Disasters, Secularism, and Cultural Change in America. *Psychol. Sci.* **26**, 311–324 (2015).
32. Varnum, M. E. W. & Grossmann, I. Cultural Change: The How and the Why. *Perspect. Psychol. Sci.* **12**, 956–972 (2017).
33. Wang, A. The Shazam music recognition service. *Commun. ACM* **49**, 44–48 (2006).
34. Gomez-Rodriguez, M., Leskovec, J. & Krause, A. Inferring Networks of Diffusion and Influence. *ACM Trans. Knowl. Discov. Data* **5**, 1–37 (2012).
35. Volkov, D. & Kolesnikov, A. Alternate Reality: How Russian Society Learned to Stop Worrying About the War. *Carnegie Endowment for International Peace*. https://carnegieendowment.org/research/2023/11/alternate-reality-how-russian-society-learned-to-stop-worrying-about-the-war (2023).
36. Richmond, W. *The Northwest Caucasus: Past, Present, Future*. (Routledge, 2008).
37. Sasse, G. & Lackner, A. War and identity: the case of the Donbas in Ukraine. *Post-Sov. Aff.* **34**, 139–157 (2018).
38. Slyvka, R., Slyvka, L. & Atamaniuk, Y. Transformations of the cultural landscape of Donbas during the armed conflict 2015–2017. *Stud. Z Geogr. Polit. Hist.* **6**, 305–326 (2017).
39. Bornstein, G. Intergroup Conflict: Individual, Group, and Collective Interests. *Personal. Soc. Psychol. Rev.* **7**, 129–145 (2003).
40. Bornstein, G. & Ben-Yossef, M. Cooperation in Intergroup and Single-Group Social Dilemmas. *J. Exp. Soc. Psychol.* **30**, 52–67 (1994).
41. Bauer, M. *et al.* Can War Foster Cooperation? *J. Econ. Perspect.* **30**, 249–274 (2016).
42. Bowles, S. Group competition, reproductive leveling, and the evolution of human altruism. *Science* **314**, 1569–1572 (2006).
43. Bowles, S. Did Warfare Among Ancestral Hunter-Gatherers Affect the Evolution of Human Social Behaviors? *Science* **324**, 1293–1298 (2009).

44. Choi, J.-K. & Bowles, S. The Coevolution of Parochial Altruism and War. *Science* **318**, 636–640 (2007).
45. Bauer, M., Cassar, A., Chytilová, J. & Henrich, J. War's Enduring Effects on the Development of Egalitarian Motivations and In-Group Biases. *Psychol. Sci.* **25**, 47–57 (2014).
46. Jackson, J. C. *et al.* Tight cultures and vengeful gods: How culture shapes religious belief. *J. Exp. Psychol. Gen.* **150**, 2057 (2021).
47. Barceló, J. The long-term effects of war exposure on civic engagement. *Proc. Natl. Acad. Sci.* **118**, e2015539118 (2021).
48. Bellows, J. & Miguel, E. War and local collective action in Sierra Leone. *J. Public Econ.* **93**, 1144–1157 (2009).
49. Denisova, A. Democracy, protest and public sphere in Russia after the 2011–2012 anti-government protests: digital media at stake. *Media Cult. Soc.* **39**, 976–994 (2017).
50. Buzgalin, A. V. & Kolganov, A. I. The Protests in Belarus: Context, Causes and Lessons. *Crit. Sociol.* **47**, 441–453 (2021).
51. Bekus, N. & Gabowitsch, M. Introduction to the Special Issue on Protest and Authoritarian Reaction in Belarus: New Subjectivities and Beyond. *Communist and Post-Communist Studies* vol. 56 1–21 (2023).
52. Harrington, J. R. & Gelfand, M. J. Tightness–looseness across the 50 united states. *Proc. Natl. Acad. Sci.* **111**, 7990–7995 (2014).
53. Ebert, T. *et al.* Are regional differences in psychological characteristics and their correlates robust? Applying spatial-analysis techniques to examine regional variation in personality. *Perspect. Psychol. Sci.* **17**, 407–441 (2022).
54. Rentfrow, P. J., Gosling, S. D. & Potter, J. A Theory of the Emergence, Persistence, and Expression of Geographic Variation in Psychological Characteristics. *Perspect. Psychol. Sci.* **3**, 339–369 (2008).
55. Rentfrow, P. J. Geographical psychology. *Curr. Opin. Psychol.* **32**, 165–170 (2020).
56. Kracauer, S. *From Caligari to Hitler: A Psychological History of the German Film*. (Princeton University Press, 2019).
57. Street, J. *Music and Politics*. (John Wiley & Sons, 2013).
58. Cerulo, K. A. Social Disruption and Its Effects on Music: An Empirical Analysis. *Soc. Forces* **62**, 885–904 (1984).
59. Coker, C. *Men at War: What Fiction Tells Us about Conflict, from The Iliad to Catch-22*.

(Oxford University Press, USA, 2014).
60. Poole, W. S. *Wasteland: The Great War and the Origins of Modern Horror*. (Catapult, 2018).
61. Kryvasheyeu, Y. *et al.* Rapid assessment of disaster damage using social media activity. *Sci. Adv.* **2**, e1500779 (2016).
62. Earle, P. S., Bowden, D. & Guy, M. Twitter earthquake detection: earthquake monitoring in a social world. *Ann. Geophys.* **54**, 708–715 (2011).
63. Sakaki, T., Okazaki, M. & Matsuo, Y. Earthquake shakes Twitter users: real-time event detection by social sensors. in *Proc. Int. AAAI Conf. WWW* 851–860 (2010).
64. Imran, M., Elbassuoni, S., Castillo, C., Diaz, F. & Meier, P. Extracting information nuggets from disaster-Related messages in social media. *Iscram* **201**, 791–801 (2013).
65. Preis, T., Moat, H. S., Bishop, S. R., Treleaven, P. & Stanley, H. E. Quantifying the digital traces of Hurricane Sandy on Flickr. *Sci. Rep.* **3**, 3141 (2013).
66. Guan, X. & Chen, C. Using social media data to understand and assess disasters. *Nat. Hazards* **74**, 837–850 (2014).
67. Olteanu, A., Vieweg, S. & Castillo, C. What to Expect When the Unexpected Happens: Social Media Communications Across Crises. in *Proc. Int. ACM Conf. CSCW* 994–1009 (2015).
68. Phan, T. Q. & Airoldi, E. M. A natural experiment of social network formation and dynamics. *Proc. Natl. Acad. Sci.* **112**, 6595–6600 (2015).
69. Signorini, A., Segre, A. M. & Polgreen, P. M. The use of Twitter to track levels of disease activity and public concern in the US during the influenza A H1N1 pandemic. *PloS One* **6**, e19467 (2011).
70. Boon-Itt, S. & Skunkan, Y. Public perception of the COVID-19 pandemic on Twitter: sentiment analysis and topic modeling study. *JMIR Public Health Surveill.* **6**, e21978 (2020).
71. Tang, L., Bie, B., Park, S.-E. & Zhi, D. Social media and outbreaks of emerging infectious diseases: A systematic review of literature. *Am. J. Infect. Control* **46**, 962–972 (2018).
72. Starbird, K. & Palen, L. (How) will the revolution be retweeted?: information diffusion and the 2011 Egyptian uprising. in *Proc. Int. ACM Conf. CSCW* 7–16 (2012).
73. González-Bailón, S., Borge-Holthoefer, J., Rivero, A. & Moreno, Y. The dynamics of protest recruitment through an online network. *Sci. Rep.* **1**, 1–7 (2011).

74. Budak, C. & Watts, D. J. Dissecting the spirit of Gezi: Influence vs. selection in the Occupy Gezi movement. *Sociol. Sci.* **2**, 370–397 (2015).
75. Schlosser, A. E. Self-disclosure versus self-presentation on social media. *Curr. Opin. Psychol.* **31**, 1–6 (2020).
76. MacDonald, R. A., Hargreaves, D. J. & Miell, D. *Musical Identities*. (OUP Oxford, 2002).
77. Eerola, T. & Vuoskoski, J. K. A review of music and emotion studies: Approaches, emotion models, and stimuli. *Music Percept. Interdiscip. J.* **30**, 307–340 (2012).
78. Margulis, E. H., Wong, P. C. M., Turnbull, C., Kubit, B. M. & McAuley, J. D. Narratives imagined in response to instrumental music reveal culture-bounded intersubjectivity. *Proc. Natl. Acad. Sci.* **119**, e2110406119 (2022).
79. Apple Newsroom. Shazam turns 20. https://www.apple.com/uk/newsroom/2022/08/shazam-turns-20/ (2022).
80. Henrich, J., Heine, S. J. & Norenzayan, A. Most people are not WEIRD. *Nature* **466**, 29–29 (2010).
81. Lee, H., Jacoby, N., Hennequin, R. & Moussallam, M. Tracing the mechanisms of cultural diversity through 2.5 million individuals' music listening patterns. Preprint at https://doi.org/10.31234/osf.io/73kyf (2024).
82. Park, M., Park, J., Baek, Y. M. & Macy, M. Cultural values and cross-cultural video consumption on YouTube. *PloS One* **12**, e0177865 (2017).
83. Bail, C. A., Brown, T. W. & Wimmer, A. Prestige, Proximity, and Prejudice: How Google Search Terms Diffuse across the World. *Am. J. Sociol.* **124**, 1496–1548 (2019).
84. Anderson, A., Maystre, L., Anderson, I., Mehrotra, R. & Lalmas, M. Algorithmic Effects on the Diversity of Consumption on Spotify. in *Proc. Int. ACM Conf. WWW (2020)*.
85. Brinkmann, L. *et al.* Machine culture. *Nat. Hum. Behav.* **7**, 1855–1868 (2023).
86. Nyhan, B. *et al.* Like-minded sources on Facebook are prevalent but not polarizing. *Nature* **620**, 137–144 (2023).
87. Pearl, J., Glymour, M. & Jewell, N. P. *Causal Inference in Statistics: A Primer*. (John Wiley & Sons, 2016).
88. Derex, M. & Boyd, R. The foundations of the human cultural niche. *Nat. Commun.* **6**, 8398 (2015).
89. Centola, D. The network science of collective intelligence. *Trends Cogn. Sci.* (2022).
90. Anglada-Tort, M., Harrison, P. M., Lee, H. & Jacoby, N. Large-scale iterated singing experiments reveal oral transmission mechanisms underlying music evolution. *Curr.*

Biol. **33**, 1472–1486 (2023).

91. Kirby, S., Cornish, H. & Smith, K. Cumulative cultural evolution in the laboratory: an experimental approach to the origins of structure in human language. *Proc. Natl. Acad. Sci. U. S. A.* **105**, 10681–10686 (2008).
92. North, A. C., Hargreaves, D. J. & Hargreaves, J. J. Uses of music in everyday life. *Music Percept.* **22**, 41–77 (2004).
93. Laplante, A. & Downie, J. S. The utilitarian and hedonic outcomes of music information-seeking in everyday life. *Libr. Inf. Sci. Res.* **33**, 202–210 (2011).
94. The World Bank. The world by region. https://datatopics.worldbank.org/sdgatlas/archive/2017/the-world-by-region.html (2017).
95. Wood, S. N., Goude, Y. & Shaw, S. Generalized Additive Models for Large Data Sets. *J. R. Stat. Soc. Ser. C Appl. Stat.* **64**, 139–155 (2015).
96. Serrano, M. Á., Boguñá, M. & Vespignani, A. Extracting the multiscale backbone of complex weighted networks. *Proc. Natl. Acad. Sci.* **106**, 6483–6488 (2009).
97. Neal, Z. P. backbone: An R package to extract network backbones. *PloS One* **17**, e0269137 (2022).
98. Kawakita, G., Zeleznikow-Johnston, A., Tsuchiya, N. & Oizumi, M. Comparing color similarity structures between humans and LLMs via unsupervised alignment. Preprint at https://doi.org/10.48550/arXiv.2308.04381 (2023).
99. Grave, E., Joulin, A. & Berthet, Q. Unsupervised Alignment of Embeddings with Wasserstein Procrustes. in *Proceedings of the Twenty-Second International Conference on Artificial Intelligence and Statistics* 1880–1890 (PMLR, 2019).
100. Hu, Y. Efficient, High-Quality Force-Directed Graph Drawing. *Math. J.* (2006).
101. Mikolov, T., Grave, E., Bojanowski, P., Puhrsch, C. & Joulin, A. Advances in Pre-Training Distributed Word Representations. in *Proc. Int. Conf. LREC* (2018).
102. Anglada-Tort, M., Lee, H., Krause, A. E. & North, A. C. Here comes the sun: music features of popular songs reflect prevailing weather conditions. *R. Soc. Open Sci.* **10**, 221443 (2023).
103. Monroe, B. L., Colaresi, M. P. & Quinn, K. M. Fightin' Words: Lexical Feature Selection and Evaluation for Identifying the Content of Political Conflict. *Polit. Anal.* **16**, 372–403 (2017).
104. Khurana, D., Koli, A., Khatter, K. & Singh, S. Natural language processing: state of the

art, current trends and challenges. *Multimed. Tools Appl.* **82**, 3713–3744 (2023).

105. Thompson, B., Roberts, S. G. & Lupyan, G. Cultural influences on word meanings revealed through large-scale semantic alignment. *Nat. Hum. Behav.* **4**, 1029–1038 (2020).
106. Jackson, J. C. *et al.* Emotion semantics show both cultural variation and universal structure. *Science* **366**, 1517–1522 (2019).
107. Bogdanov, D. *et al.* Essentia: An Audio Analysis Library for Music Information Retrieval. in *Proc. ISMIR* 493–498 (2013).
108. Melville, J., Lun, A., Djekidel, M. N., Hao, Y. & Eddelbuettel, D. uwot: The Uniform Manifold Approximation and Projection (UMAP) Method for Dimensionality Reduction. (2023).
109. Ripley, B. MASS: support functions and datasets for Venables and Ripley's MASS. *R Package Version* **7**, 3–29 (2011).
110. Drost, H.-G. Philentropy: information theory and distance quantification with R. *J. Open Source Softw.* **3**, 765 (2018).
111. Haerpfer, C., Inglehart, R., Moreno, A., Welzel, C., Kizilova, K., Diez-Medrano, J., ... & Puranen, B. World Values Survey Wave 7 (2017-2022) cross-national data-set. World Values Survey Association (2022).
112. Stebelsky, I. Ethnic Self-Identification in Ukraine, 1989–2001: Why More Ukrainians and Fewer Russians? *Can. Slavon. Pap.* **51**, 77–100 (2009).
113. Tyshchuk, T. & Sologoub, I. Censuses in Ukraine: Not trusted and not needed? in *The Global Politics of Census Taking* (Routledge, 2024).
114. Loo, M. van der *et al.* stringdist: Approximate String Matching, Fuzzy Text Search, and String Distance Functions. (2023).
115. Lee, H., Höger, F., Schönwiesner, M., Park, M. & Jacoby, N. Cross-cultural Mood Perception in Pop Songs and its Alignment with Mood Detection Algorithms. in *Proc. ISMIR* 366–373 (2021).
116. Lakens, D. Calculating and reporting effect sizes to facilitate cumulative science: a practical primer for t-tests and ANOVAs. *Front. Psychol.* **4**, 863 (2013).

Supplementary information

Supplementary information can be viewed by following the link: https://osf.io/ebrgw.

Authors' contributions

Conceptualization, investigation, administration, methodology, analysis, interpretation, and writing: H.L., M.A., M.P. and N.J. Initial conception of the idea: M.S., O.S., H.L., and M.A. Data collection and curation: H.L. Interactive plots: P.R. Data interpretation: O.S., M.S. Project supervision: O.T., M.P., N.J. All authors worked collaboratively to discuss methods, analysis, and writing throughout the process of preparing the published work.