Doctoral Dissertation Academic Year 2023

Cultural (co-)evolution of music and language: review and global acoustic analysis

Yuto Ozaki

Graduate School of Media and Governance
Keio University

A dissertation submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

Abstract

Humans use two universal acoustic communication systems daily: music and (spoken) language. What are the key features of these two universal acoustic communication forms? And how have music and language emerged throughout human evolutionary history? This dissertation contributes to these two long-standing scientific questions.

This dissertation consists of two central chapters, following the overview and background in Chapter 1. In Chapter 2, I provide an extensive review of the studies on the cultural evolution of music and language. Cultural evolutionary research of music and language has been producing various findings regarding how music and language evolve empirically, experimentally, and computationally. However, these two disciplines have developed mostly independently, so this is the first time contrasting and synthesizing their studies, which provides a more integrated view of how these communication systems emerged and their potential co-evolving pathways.

Chapter 3 analyzes similarities and differences between song, instrumental music, and speech sampled from over 60 collaborators whose 1st or heritage languages belong to around 20 language families. Although it is essential to take into account cultural variations, few studies have undertaken analyses with a diverse set of languages. Thus, this study provides the most compelling empirical evidence to date. The analyses identified the three features of pitch height, temporal rate, and pitch stability exhibiting cross-cultural differences and the two features of timbral brightness and pitch interval size as cross-cultural similarities between song and speech. Furthermore, the distributions of the three differentiating features displayed a continuous shift from music to language.

I present potential future directions and proposals about global collaborative research and inclusivity for the equity of “humanly organized sounds” in Chapter 4, including novel speculation about the evolutionary origin of music built upon commonalities across non-linguistic vocal communication and our findings. This dissertation sheds light on what has shaped music and language.

Keywords: Music, Language, Cultural evolution, Cross-cultural comparison, Audio analysis

Academic Degree Evaluation Committee:

- Main Advisor: Assoc. Prof. Patrick Savage, Keio University
- Co-Advisor:
    1. Assoc. Prof. Shinya Fujii, Keio University
    2. Guest Assoc. Prof. Nao Tokui, Keio University
    3. Prof. Akira Wakita, Keio University

Table of contents

Preface and acknowledgments

This dissertation comprises multiple collaborative projects spanning several fields. Chapters 1 and 4 were written solely by me. Chapter 2 was led by me, and the initial draft was also written by myself. This chapter discusses a wide range of topics from the cultural evolution of music, language, and those intersections, so Marianne de Heer Kloots, Andrea Ravignani, and my supervisor Patrick Evan Savage (PES) refined the manuscript by fusing their expertise on each discipline. Chapter 3 was led by PES for project administration, and I led drafting and analysis. Amongst a large number of collaborators, Adam Tierney, Peter Q. Pfordresher, John McBride, Emmanouil Benetos, Polina Proutskouva, Fang Liu, Suzanne C. Purdy, Patricia Opondo, Shantala Hegde, Florence Nweke, Dhwani P. Sadaphal, and Shafagh Hadavi especially weighed in editing, suggestions, and pilot data collection. Full contribution information is disclosed at author contributions section of each chapter. Chapters 2 and 3 are available as preprints ultimately intended for publication as Ozaki et al. (In press) and Ozaki et al. (2023), respectively. Chapter 2 is included with permission from Oxford University Press (https://academic.oup.com/pages/authoring/books/author-reuse-and-self-archiving?cc=us&lang=en&). Chapter 3 is available as a preprint under the CC BY license.

I would like to acknowledge my gratitude for all the support I have been given over the past three years. I would like to sincerely thank my supervisor, Patrick Savage, for the excellent guidance and support during my PhD programme. He provided me with opportunities to engage in various exciting projects and enabled me to join international conferences, both of which have considerably broadened my horizon in the world of music science. I would never have made all of my academic achievements without his diligent supervision. I have also appreciated my committee members, Shinya Fujii and Nao Tokui, and our numerous manuscript readers and collaborators for their willingness to share their time, advice, and data. Above all, I would like to sincerely thank my family and friends for rooting for me all the time.

This research was funded by the grant to Yuto Ozaki from Japan Science and Technology Agency (Grant Number JPMJSP2123 of Support for Pioneering Research Initiated by the Next Generation) and the grant to Patrick Savage from Japan Society for the Promotion of Science (KAKENHI Grant-in-Aid #19KK0064).

1. Introduction: Analyzing the diversity and specificity of music and language as the human communication continuum.

Acoustic communication is widespread in animals (Chen & Wiens, 2020; Kelley, 2022), ranging from insects (e.g. crickets) to living things under the sea (e.g. whales). Humans can hear sounds in the frequency range from around 20 Hz to 20,000 Hz, but some species utilize tones even outside of this range (e.g. mice). We, humans, also considerably draw upon various acoustic communication in our daily lives, which can be roughly grouped into music and (spoken) language. These two communication forms are universally present in our societies (Brown, 1991; Mehr et al., 2019). However, despite their ubiquitous presence in every culture, the striking aspect is that they take very diverse forms, and some scholars contemplated there are almost no shared properties in every language and music (Evans & Levinson, 2009; Nettl, 2015). Still, we can reliably identify whether the uttered sounds are song or spoken language regardless of familiarity with or knowledge about the given music and language (Albouy et al., 2023). What are the key features of these two universal acoustic communication forms? And how have music and language emerged in our society throughout human evolutionary history? This dissertation contributes to these two long-standing scientific questions.

Although this dissertation focuses on comparing music and (mainly spoken) language, the other research projects I have completed put more emphasis on the cross-cultural diversity of music. In particular, I engaged upon reliability analysis of automated music transcription methods to global musical samples of singing (Ozaki et al., 2021), dominancy of visual or audio in music performance evaluation in different music traditions (Chiba, Ozaki [co-first author] et al., 2023), and the book chapter dedicated to the cultural evolution of music (Youngblood et al., 2023; second author). The key research interest is to advance our understanding of cross-cultural diversity of music. For example, the first project revealed relatively low reliability of automated music transcription methods for analyzing traditional songs sampled globally (Ozaki et al., 2021), which suggests more work is expected to include non-Western corpora in music information retrieval research. The second study found a potential culturally dependent pattern in which audio or visual is more influential when people assess the superiority of musical performance (Chiba et al., 2023). Previous research (Mehr et al., 2018; Tsay, 2013) studied the same psychological effect but with Western music and Western participants only, and our extended study illustrates music cognition also benefits from performing a replication study in different cultural settings to gain another interpretation of the preceding results. We used the Registered Report format in the second study, which takes peer review and decides (in-principle) acceptance before data are collected and analyzed to prevent researchers from publication bias. This experience later indeed helped us decide what to publish in the research of Chapter 3 on a more theoretical basis; otherwise, we would be tempted to hold back the negative result we actually found even if it still provided meaningful information.

Cross-cultural studies are effective in investigating cultural differences and commonalities of music, and my primary motivation for embarking on a PhD was to derive scientific insights into such aspects of music. Since I started my master's, I have been attracted to the diversity of music and been intrigued by how we can obtain an organized overview of the universe of music, which led me pursuing to learn an array of data analysis methods (signal processing, statistical inference, deep learning, Bayesian modeling, etc.). Encounter with the field of cultural evolution was a fascinating moment since it seemed the most promising theory explaining the mechanism of the increase in variation of cultural traits. However, combining the notion of evolution with music brought me another interest: What if any, is the evolutionary origin of music? What is the ultimate root of this diversity? We may not be able to know what makes music unique or special if we only study music, which is an important aspect when discussing the evolutionary root of music. To answer this question, we need to understand the specificity of music through comparative analysis with related acoustic communication.

In the second chapter, I will provide an extensive review of the studies on the cultural evolution of music and language. It is unlikely that music and language appeared in the current forms at some point in the past suddenly. Rather, a more plausible scenario is that they have gradually changed from some initial states to the states nowadays observed, though punctuated changes may have also happened. Cultural evolution tackles uncovering how and why culture has mutated over time, and a line of research on the cultural evolution of music and language has been producing various findings regarding how music and language evolve empirically, experimentally, and mathematically. However, cultural evolutionary studies of music and language have developed mostly independently, so this is the first time contrasting and synthesizing the studies of these two fields, which will provide a more integrated view of how these communication cultures emerged and potential co-evolving pathways.

The third chapter analyzes similarities and differences between song and speech sampled from over 60 collaborators whose 1st or heritage languages belong to around 20 language families in total. Comparative analyses of music and language have been undertaken frequently in various fields. However, although it is essential to take into account cultural variations of music and languages, few studies have undertaken analyses with a diverse set of languages like ours. Thus, this study provides the most compelling empirical evidence to date about the regularities underlying music and language on the globe. The analyses identified the three features of pitch height, temporal rate, and pitch stability exhibiting cross-cultural differences and the two features of timbral brightness and pitch interval size as cross-cultural similarities between song and speech. Furthermore, the additional analyses including lyrics recitation of the sung song and the instrumental version of the sung melody in comparison revealed a cross-culturally consistent musi-linguistic continuum (Brown, 2000) in the distributions of the three differentiating features.

In the final chapter, I will present potential future directions and proposals about global collaborative research followed by the discussions developed in Chapters 2 and 3. This includes my speculation about the evolutionary origin of music, which is a novel perspective on the emotive communication nature of music (Besson & Schön, 2001; Leongómez et al., 2022; Ma et al., 2019). Debates on the evolutionary nature of music have a long history that we can trace back to Darwin (1871). Although we have reached a decisive conclusion yet, I hope this chapter can supply some ideas for the future of this field.

References

Albouy, P., Mehr, S. A., Hoyer, R. S., Ginzburg, J., & Zatorre, R. J. (2023). *Spectro-temporal acoustical markers differentiate speech from song across cultures*. bioRxiv preprint. https://doi.org/10.1101/2023.01.29.526133

Besson, M., & Schön, D. (2001). Comparison between Language and Music. *Annals of the New York Academy of Sciences*, *930*(1), 232–258. https://doi.org/10.1111/j.1749-6632.2001.tb05736.x

Brown, D. E. (1991). *Human Universals*. McGraw-Hill.

Brown, S. (2000). The Musilanguage Model of Music Evolution. In S. Brown, B. Merker, & C. Wallin (Eds.), *The Origins of Music* (pp. 271–300). The MIT Press.

Chen, Z., & Wiens, J. J. (2020). The origins of acoustic communication in vertebrates. *Nature Communications*, *11*(1), Article 1. https://doi.org/10.1038/s41467-020-14356-3

Chiba, G., Ozaki, Y., Fujii, S., Savage, P. E. (2023). Sight vs. sound judgments of music performance depend on relative performer quality: Cross-cultural evidence from classical piano and Tsugaru shamisen competitions. *Collabra: Psychology.* https://doi.org/10.1525/collabra.73641 *(Peer Community In Registered Reports* editorial recommendation and peer review: https://doi.org/10.24072/pci.rr.100351)

Darwin, C. (1871). *The descent of man*. Watts & Co.

Evans, N., & Levinson, S. C. (2009). The myth of language universals: Language diversity and its importance for cognitive science. *Behavioral and Brain Sciences*, *32*(5), 429–448. https://doi.org/10.1017/S0140525X0999094X

Kelley, D. B. (2022). Convergent and divergent neural circuit architectures that support acoustic communication. *Frontiers in Neural Circuits*, *16*. https://www.frontiersin.org/articles/10.3389/fncir.2022.976789

Leongómez, J. D., Havlíček, J., & Roberts, S. C. (2022). Musicality in human vocal communication: An evolutionary perspective. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *377*(1841), 20200391. https://doi.org/10.1098/rstb.2020.0391

Ma, W., Fiveash, A., & Thompson, W. F. (2019). Spontaneous emergence of language-like and music-like vocalizations from an artificial protolanguage. *Semiotica*, *2019*(229), 1–23. https://doi.org/10.1515/sem-2018-0139

Mehr, S. A., Scannell, D. A., & Winner, E. (2018). Sight-over-sound judgments of music performances are replicable effects with limited interpretability. *PLOS ONE*, *13*(9), e0202075. https://doi.org/10.1371/journal.pone.0202075

Mehr, S. A., Singh, M., Knox, D., Ketter, D. M., Pickens-Jones, D., Atwood, S., Lucas, C., Jacoby, N., Egner, A. A., Hopkins, E. J., Howard, R. M., Hartshorne, J. K., Jennings, M. V., Simson, J., Bainbridge, C. M., Pinker, S., O'Donnell, T. J., Krasnow, M. M., & Glowacki, L. (2019). Universality and diversity in human song. *Science*, *366*(6468), eaax0868. https://doi.org/10.1126/science.aax0868

Nettl, B. (2015). *The Study of Ethnomusicology: Thirty-Three Discussions* (3rd ed.). University of Illinois Press. https://www.press.uillinois.edu/books/?id=p080821

Ozaki, Y**.**, McBride, J., Benetos, E., Pfordresher, P., Six, J., Tierney, A. T., Proutskova, P., Sakai, E., Kondo, H., Fukatsu, H., Fujii, S., & Savage, P. E. (2021, November 7-12). Agreement among human and automated transcriptions of global songs. *Proceedings of the 22nd International Society for Music Information Retrieval (ISMIR) Conference*, Online, 500-508. https://archives.ismir.net/ismir2021/paper/000062.pdf

Ozaki, Y., Tierney, A., Pfordresher, P. Q., McBride, J., Benetos, E., Proutskouva, P., Chiba, G., Liu, F., Jacoby, N., Purdy, S. C., Opondo, P., Fitch, W. T., Rocamora, M., Thorne, R., Nweke, F., Sadaphal, D., Sadaphal, P., Hadavi, S., Fujii, S., ... Savage, P. E. (2023, 採録許可). Globally, songs and instrumental melodies are slower, higher, and use more stable pitches than speech [Stage 2 Registered Report]. *Peer Community In Registered Reports*. Preprint: https://doi.org/10.31234/osf.io/jr9x7

Tsay, C.-J. (2013). Sight over sound in the judgment of music performance. *Proceedings of the National Academy of Sciences*, *110*(36), 14580–14585. https://doi.org/10.1073/pnas.1221454110

Youngblood, M., Ozaki, Y., & Savage, P. E. (2023). Cultural evolution and music. In J. R. Kendal, J. Tehrani, & J. Kendal (Eds.), *Oxford Handbook of Cultural Evolution.* Oxford University Press. Preprint: https://doi.org/10.31234/osf.io/xsb7v

2. Cultural evolution of music and language[1]

Abstract
Music and language are both forms of communication universally observed across human societies, prompting researchers to investigate why and how they evolved. Such research initially focused on the *biological* evolution of the capacities to create and perceive language and music; later work has been increasingly tackling the *cultural* evolution angle to study the mechanisms and processes driving the diversity and regularities of music and language. In this chapter, we review seminal studies of the cultural evolution of music and language. We group the review into observational studies (e.g., phylogenetic analysis), experimental studies (e.g., transmission chains), simulation studies (e.g., agent-based models), and music-language relationships (e.g., song/speech melody/prosody). Furthermore, we highlight key ideas that each discipline can learn from the other and promising research topics to encourage collaborative work. In particular, we argue that more direct comparisons of music and language will help to better understand commonalities and differences in their evolution. This includes parallels (or lack thereof) in cognitive and motor constraints (e.g., memorability, ease of vocalization), cultural transmission mechanisms (e.g., vertical/horizontal transmission with/independent from human populations), and underlying biological bases (e.g., vocal learning). Integrating the emerging field of cultural evolution of music with the larger literature on language evolution will enrich our understanding of both music and language.

2.1. Introduction: Overview of the fields

Music and language are both human universal cultural systems (D. Brown, 1991; Patel, 2008; Savage, 2019; Mehr et al., 2019). All known societies make use of these two types of communication - including combined in the form of songs with words - leading scholars from Darwin (1871) to the current volume to speculate on their evolutionary origins and relationships. Historically, such discussion has focused primarily on the *biological* evolution of the capacities to make and experience music ("musicality"; c.f., Wallin et al., 2000; Patel, 2008; Honing et al., 2015;) and language ("the faculty of language"; c.f., Hauser et al., 2002; Christiansen & Kirby, 2003; Fitch, 2010). However, a growing body of research has explored the *cultural* evolution of musical and linguistic forms themselves (e.g., melodies/words; instruments/writing systems; musical genres/linguistic families), and the way such cultural evolutionary processes may relate to biological evolution or even feedback onto it via gene-culture coevolution (Dediu et al. 2011; Patel, 2018; Savage et al., 2021).

Several chapters in this *Oxford Handbook of Language and Music* provide comprehensive reviews of biological evolutionary relationships between music and language (Fitch, this volume; Brown, this volume; ten Cate & Honing, this volume; Gingras & Drayna, this volume). Meanwhile, several chapters in the forthcoming *Oxford Handbook of Cultural Evolution* provide comprehensive reviews of the cultural evolution of music (Youngblood et

[1] Ozaki, de Heer Kloots, Ravignani & Savage, *Oxford Handbook of Language and Music (Under contract)*

Authors: Yuto Ozaki[1], Marianne de Heer Kloots[2], Andrea Ravignani[3], Patrick E. Savage[1]
[1]Graduate School of Media and Governance / Faculty of Environment and Information Studies, Keio University, Japan
[2]Institute for Logic, Language and Computation, University of Amsterdam, The Netherlands
[3]Comparative Bioacoustics Group, Max Planck Institute for Psycholinguistics, The Netherlands

al. 2023), language (Bailes & Cuskley, 2023; Greenhill, In Press; Raviv & Kirby, 2023In Press; Kim & Morin, 2023), and general principles of gene-culture coevolution (Lala et al., In Press; Lotem et al., 2023). Our aim in this chapter is to compare and synthesize these studies to reveal how a comparative, cultural evolutionary perspective on music and language can lead to a better understanding of both domains, their evolutionary relationships, and possible coevolution.

Cultural evolution provides the theoretical foundation for how culture, such as ideas, behaviors and artifacts, can change over time (Mesoudi, 2011; Creanza et al., 2017). This is not merely a metaphor: rather, Darwin's theory of biological evolution was explicitly inspired by earlier studies of language evolution, such as the discovery that languages as different as English and Hindi shared a common ancestral "Proto-Indo-European" language (see Section 2 for details). As Darwin wrote in *The Descent of Man* (1871):

> "*The formation of different languages and of distinct species, and the proofs that both have been developed through a gradual process, are curiously parallel . . . . We find in distinct languages striking homologies due to community of descent, and analogies due to a similar process of formation*." (pp. 89–90)

In 1955, the International Council for Traditional Music also defined "folk music" using cultural evolutionary terms:

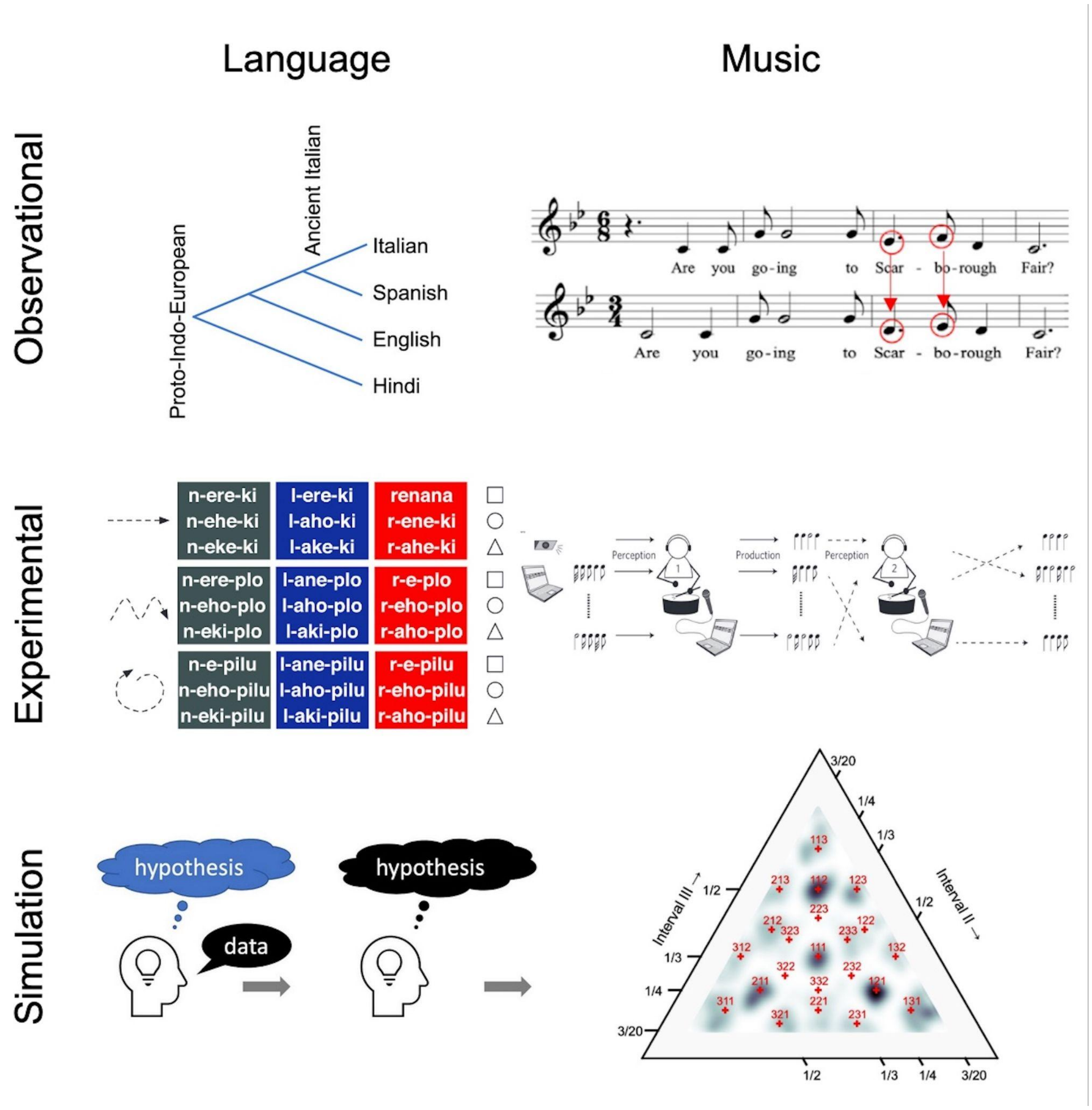
> "*Folk music is the product of a musical tradition that has been evolved through the process of oral transmission. The factors that shape the tradition are: (i) continuity which links the present with the past; (ii) variation which springs from the creative impulse of the individual or the group; and (iii) selection by the community, which determines the form or forms in which the music survives.*" (Cherbuliez et al., 1955:23)

Cultural evolution can also influence the selection of genes and vice versa, with the cultural adoption of dairy farming famously leading to selection for genes to digest milk lactose in adults (Ségurel & Bon, 2017). Such mutual interaction between genetic evolution and cultural evolution is named gene-culture coevolution, dual inheritance theory, or cultural niche construction (Feldman & Laland, 1996; Crenza et al., 2017; Laland & O'Brien, 2011; Richerson & Boyd, 1978). In the case of the evolutionary study of music and language, some studies are concerned with purely the evolution of music or language itself drawing on evolutionary analysis methods (e.g. Bomin et al., 2016; Greenhill et al., 2017), but there are different kinds of studies not necessarily conforming to this category (e.g., Serrà et al., 2012). Hence, in this chapter, we broadly discuss research on music and language as evolving human cultural traits regardless of explicitly grounding in cultural evolutionary theory.

Mesoudi (2021) explained that the field of cultural evolution nowadays comprises two main types of research: traditional (and original) population-genetic-style, and cognitive scientific approach. Research engaging in cultural evolution of music and language from the former viewpoint is relatively sparse. However, laboratory experiments to divulge cognitive priors generating fundamental aspects of music and language have been actively conducted. Interestingly, Mesoudi (2021) also pointed out that the scholars of cultural evolution of this group also practice (Bayesian) agent model-based simulation and the analysis of cross-cultural regularities, which is also a common trend in music and language fields.

Like its sister discipline of evolutionary biology, cultural evolution often begins through observational analysis of uncontrolled, real-world "field" data. Such data might compare between-group "macroevolution" (e.g., among distinct languages or musical cultures) or within-group "microevolution" (e.g., among individual speakers/singers/dialects/melodies). Hypothesis testing often proceeds through controlled laboratory experiments and/or computational modeling.

We first review the cultural evolutionary study of music and language independently, grouped into three types of methodologies: 1) observational, 2) experimental, and 3) simulation studies. For each type, we highlight one seminal study to demonstrate the diversity of methods and findings (Fig. 2.1). We then discuss two types of potential music-language coevolution: 1) *indirect* relationships among musical, linguistic, and/or genetic histories; and 2) *direct* relationships between musical and linguistic features such as musical/linguistic rhythm or musical melody/linguistic prosody. Finally, we outline contrasts between the cultural evolution studies of music and language, what each discipline can learn from the other, and propose future directions toward integrating these two disciplines.



n-ere-ki n-ehe-ki n-eke-ki	l-ere-ki l-aho-ki l-ake-ki	renana r-ene-ki r-ahe-ki	□ ○ △
n-ere-plo n-eho-plo n-eki-plo	l-ane-plo l-aho-plo l-aki-plo	r-e-plo r-eho-plo r-aho-plo	□ ○ △
n-e-pilu n-eho-pilu n-eki-pilu	l-ane-pilu l-aho-pilu l-aki-pilu	r-e-pilu r-eho-pilu r-aho-pilu	□ ○ △

Figure 2.1. Simplified diagrams contrasting seminal studies of cultural evolution of music and language from each of three different methodological approaches. From top to bottom: Language: Bouckaert et al. (2012); Kirby et al. (2008); Griffiths & Kalish (2007). Music: Savage et al. (2022); Ravignani et al. (2016); Kaplan et al. (2022).

2.2. Observational studies

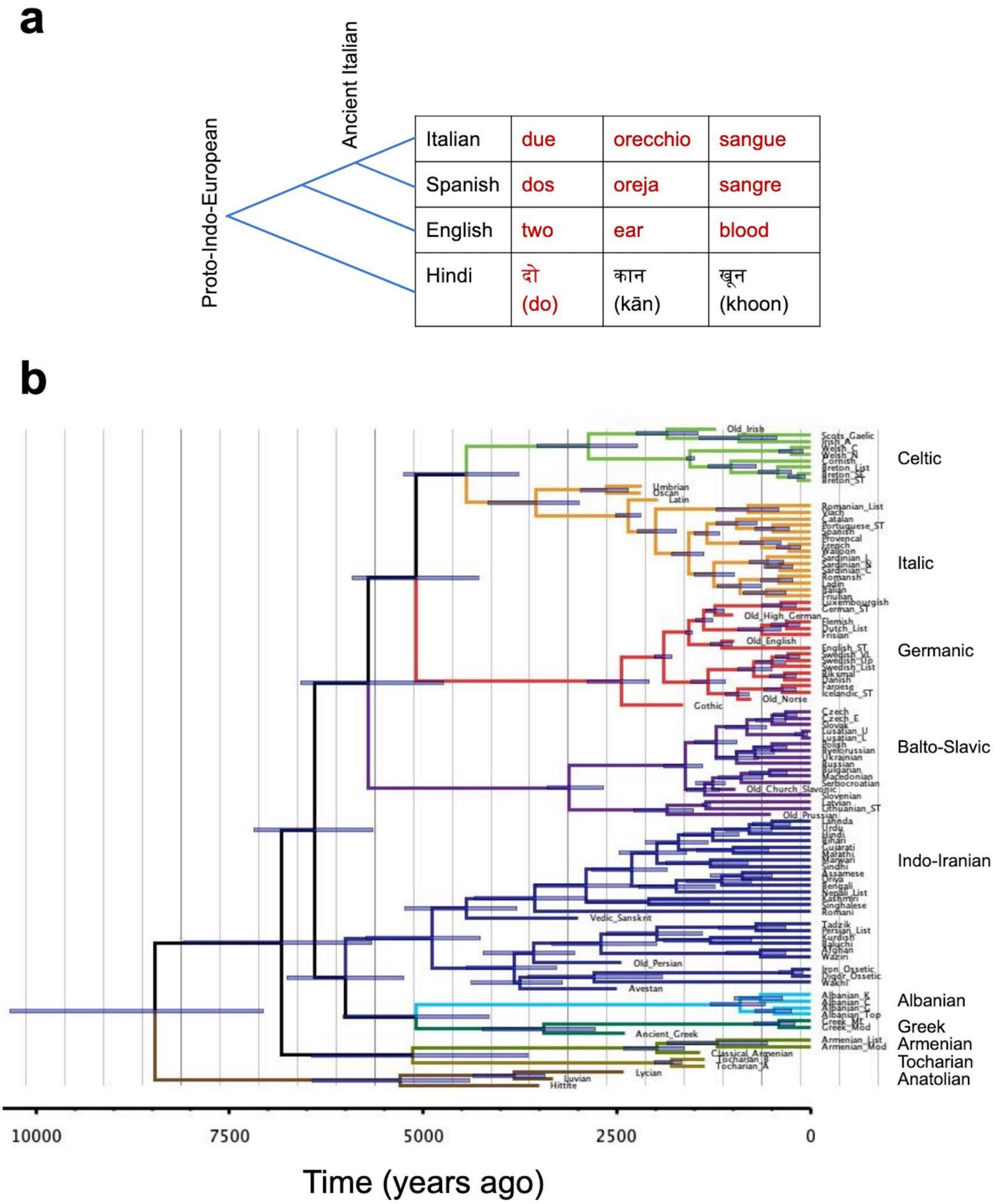
Existing linguistic and musical systems naturally provide the most ecologically valid source of data to inform cultural evolutionary theories. Here, we focus on approaches that attempt to reconstruct particular linguistic and musical histories. Some studies focus on macro-level evolution (e.g. Bouckaert et al., 2012), but there is also research concerned with micro-scale analysis (e.g. Savage et al., 2022) aiming to reveal the detailed mechanisms of evolution. One striking aspect is that the studies of this group can not only shed light on the history of language and music themselves, but also link music and language to the past events in general human history as a part of human culture.

These studies aim at unveiling evolutionary trends from data, but their methods, approaches and scope wildly differ. Some scholars are interested in reconstructing the macro-history of specific languages or musics (Bouckaert et al., 2012; Lomax, 1968; Savage, 2018), while others put emphasis on delineating the patterns from historical data (Gell-Mann & Ruhlen, 2011; Mauch et al., 2015). The types of studies further include relationships with population expansion (Gray et al., 2009; Juhász et al., 2019), ancestral state estimation from archeological evidence (Alaica et al., 2022; Barham & Everett, 2021; d'Errico et al., 2003), patterns of cultural transmission (Bryden et al., 2018; Youngblood, 2019), rate of evolution (Lambert et al., 2020), and so on. Although the range of research interests in this category is too wide to concisely summarize the overview, we pick up some studies to illustrate characteristic aspects of the evolution of music and language in the following sections.

2.2.1 Language

Reconstructing the history of language evolution has been an active area of research since before Darwin's time - indeed, Darwin's theory of biological evolution was inspired by such "philological" research (see quote in the Introduction). The Indo-European language family - including contemporary languages as distant as English and Hindi and richly documented ancient languages like Latin, Sanskrit, and ancient Greek - has been particularly well-studied. Sir Williams Jones famously concluded in 1786 that these three ancient languages had "sprung from some common source, which, perhaps, no longer exists." (cf. Atkinson & Gray, 2005). And just as modern evolutionary biology has moved to quantitative phylogenetic analysis of DNA sequences to reconstruct the evolution of biological species, so has modern cultural evolution applied quantitative phylogenetic analysis to lists of word meanings to reconstruct the evolution of language families (Gray & Atkinson, 2003; Levinson & Gray, 2012).

Bouckaert et al. (2012) applied such modern methods to the longstanding debate over Indo-European origins by applying Bayesian phylogeographic methods to a comparative database containing over 200 items of basic vocabulary from over 20 ancient and 83 contemporary Indo-European languages to reconstruct a phylogenetic tree of the language family. Such trees join more closely related languages sharing many cognates (e.g., Italian and Spanish) with shorter branches than more distantly related languages sharing fewer cognates (e.g., English, Hindi; Fig. 2.2). The dates on this tree were calibrated based on ancient texts, and both the timing and the phylogeography of the resulting tree were argued to support an "agricultural expansion from Anatolia beginning 8000 to 9500 years ago" (Bouckaert et al., 2012), although this interpretation remains controversial (cf. Pereltsvaig & Lewis, 2015).



Italian	due	orecchio	sangue
Spanish	dos	oreja	sangre
English	two	ear	blood
Hindi	दो (do)	कान (kān)	खून (khoon)

Figure 2.2. An example of phylogenetic analysis of the evolution of the Indo-European language family. a) a simplified phylogenetic tree based on comparing cognates (inherited vocabulary sharing the same meaning, origin, and sound correspondences, in red) for three concepts among four languages. b) full, dated tree of 103 Indo-European languages based on Bayesian phylogenetic analysis of over 200 concepts (based on the figure from Bouckaert et al., 2012 [Fig. S1])

Phylogenetic analysis is one of the key instruments in the cultural evolutionary analysis of language. Traditionally employed tree prior models can only represent the binary tree diversification, but extended models allowing the borrowing of linguistic traits from isolated lineages (i.e. horizontal transfer) demonstrating superior capability of reconstructing past language contact events are now available (Neureiter et al., 2022). Phylogenetic analysis can also be used to test hypotheses regarding the variation of features across languages, such as information locality and dependency locality principles of word order (Hahn & Xu, 2022), concerted evolution of phonemes (Hruschka et al., 2015), and the universality of kinship terminology (Passmore & Jordan, 2020).

In addition to the phylogenetic technique, several diverse approaches have investigated the influence of cultural factors in for example linguistic structure, from careful analyses documenting the development of recently emerged sign languages (e.g. Senghas, Kita, & Özyurek, 2004; Sandler, Meir, Padden, & Aronoff, 2005; Ergin, 2022; and see Meir, Sandler, Padden, & Aronoff, 2010), to large cross-cultural correlational studies investigating connections between linguistic and demographic properties (e.g. Hay & Bauer, 2007; Lupyan & Dale, 2010; Bentz & Winter, 2013). However, a precise understanding of the factors driving the cultural evolution of language necessitates disentangling numerous variables. For example, Josserand et al. (2021)'s analysis suggests the presence of a word corresponding to "blue" depends on the degree of UV-B radiation, distance to large bodies of standing water, and population size of speakers, which further interlink to environmentally and genetically determined color deficiency.

2.2.2 Music

Like linguists, musicologists have long attempted to reconstruct the evolutionary history of music. Such efforts included musical instruments (Sachs, 1940), singing styles (Lomax, 1968), rhythms (Toussaint, 2013) and "tune families" (Bayard, 1954). Tune family research was particularly inspired by language evolution to try to reconstruct "proto-melody" (Boilès, 1973) and the process of "evolution of one air out of another by variation, deletion, and addition" (Bayard, 1954). Like ancient languages, some early music was preserved via written notation (e.g., Sumerian cuneiform, Japanese *gagaku*, Gregorian chant, Western common practice classical music), but the invention of audio recording technology in the late 19th century dramatically expanded the ability to document musical evolution in rich detail. By the mid 20th century musicologists had recorded and compared detailed variation of musical features such as melody, rhythm, singing style, and other musical factors across thousands of musical items throughout the world (Lomax, 1968; Bronson, 1966; cf., Savage, 2019 for review).

Researchers have also applied explicit quantitative evolutionary models at large scales to such musical data, just as they have done with language. For example, Savage et al. (2022) digitized two large and detailed databases containing over 10,000 melodies from traditions they knew well as performers: English and Japanese folk songs (Bronson, 1959; Machida, 1944). By modeling melodic evolution as sequences of notes, analogous to molecular sequences of DNA or amino acids, they were able to apply sequence alignment to identify 328 pairs of highly similar melodies within various tune families, and quantify the substitution or insertion/deletion of notes between these pairs. They found that, across both Japanese and English repertoires, "note changes are more likely when they have smaller impacts on a song's melody". Specifically, note changes are more likely at rhythmically weak points, and substitutions are most likely to occur to melodically neighboring notes (Fig. 2.3). Such convergent evolutionary patterns may underscore the presence of biologically determined musicality of humans, and laboratory experiments can subsequently highlight what cognitive and motor mechanisms are attributable to the observed converged evolution from data (Hoeschele & Fitch, 2022; Anglada-Tort et al., 2023).

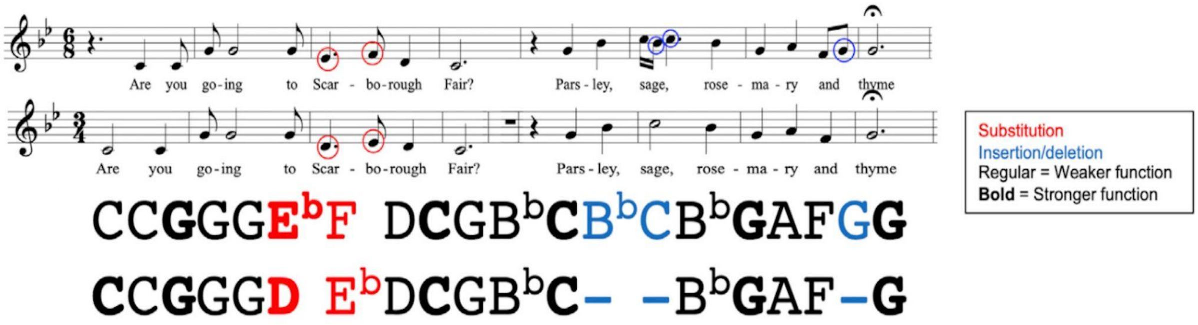

Are you go-ing to Scar - bo-rough Fair? Pars - ley, sage, rose - ma - ry and thyme
Are you go-ing to Scar - bo-rough Fair? Pars - ley, sage, rose - ma - ry and thyme
CCGGGE♭F DCGB♭CB♭CB♭GAFGG
CCGGGD E♭DCGB♭C- -B♭GAF-G
Substitution
Insertion/deletion
Regular = Weaker function
Bold = Stronger function

Figure 2.3. Sequence alignment analysis of two different versions of the same folk song melody ("Scarborough Fair") highlighting patterns of substitution and deletion during oral transmission. The top version was sung by Martin Carthy in 1965, who taught it to Simon & Garfunkel who recorded the slightly different bottom version the following year. The two substitutions (red) both occur to neighboring notes (Eb to D and F to Eb), while all of the deletions (blue) occur at rhythmically weaker ornamental notes without affecting the lyrics (figure from Savage et al., 2022).

At the beginning of this section, we spotlighted papers sharing common interests with the language side, but there are also perspectives unique to music. For example, Phillips & Brown (2022) suggest that the degree of vocal pitch precision can be a factor constraining the cultural evolution of musical scales. Another example is the dynamics of cultural change. Various transmission biases play a role in cultural evolution (e.g., novelty, payoff, (anti)conformity, prestige, content), but Klimek et al. (2019) identified a different strategy driving the cultural change in musical styles called counter-dominance cycle, which may be a sort of social learning strategy peculiar in the cultural evolution of aesthetics domain.

2.3. Experimental studies

Controlled experiments can allow us to isolate and test the role of cultural evolutionary factors that can be difficult to disambiguate from uncontrolled observational data. The experiment is a proof of concept; it tests under which condition and settings the same cultural traits observed in the real world also arise in the lab. Specifically, this approach includes exploratory generation of variation in traits and confirmatory testing of causal mechanisms. For example, controlled experiments (Anglada-Tort et al., 2023) can establish causal mechanisms underlying cross-cultural regularities in song evolution identified by corpus analyses (Savage et al., 2022) described above. Mesoudi (In Press) provides an introduction to experimental studies in the field of cultural evolution overall.

The most frequently used method is transmission chain experiments, where participants are asked to reproduce stimuli (e.g., words, rhythms, stories), and subsequent participants receive the outputs of previous "generations" (Bartlett, 1932). This transmission chain paradigm has a key strength: while participants transmit behaviors, it lets experimenters observe how the initial state of stimuli transitions to particular forms. Systematic patterns in transitioning to stable forms (or 'convergent transformations'; Acerbi et al., 2021) observed in transmission chain experiments can potentially reveal "cultural attractors" (Boyd & Henrich, 2002; Claidière & Sperber, 2007), which is another key theoretical driving force of cultural evolution alongside selection pressure. In summary, these experiments deliver key insights about underlying factors (e.g., cognitive biases, motor constraints) shaping cultural evolution.

2.3.1 Language

Language evolution experiments commonly aim to replicate the emergence of some form of linguistic structure in controlled lab settings, where the driving forces leading to particular structural properties can be more carefully manipulated and disentangled. Participants in language evolution experiments often learn to use some miniature artificial language or otherwise unfamiliar communicative device to describe a set of meanings. Research in the *experimental semiotics* tradition has studied the emergence of conventions and systematic structure as participants come up with a signalling system from scratch (Galantucci, 2005; Selten & Warglien, 2007; Galantucci & Garrod, 2011), usually in dyads or other closed-group settings without generational transmission. Another popular approach involves the *iterated learning* of miniature artificial languages by generations of participants. In the seminal study introducing the latter paradigm, Kirby, Cornish and Smith (2008) used a transmission chain design (Bartlett, 1932; Mesoudi & Whiten, 2008) in which each participant learned a set of labels to describe simple scenes, based on the labels produced by the previous participant. Initially holistic and incompressible languages (describing every scene with a separate label) became increasingly simplified over generations of transmission, to the point of degeneracy (describing each scene with the same label; see Figure 2.4). However, when duplicate labels were removed from the training input to each generation, the artificial languages developed compositional structure, with systematic form-meaning mappings between labels and scenes (see Fig. 32.4) — a prominent design feature of natural languages.

In a later experiment, Kirby, Tamariz, Cornish, & Smith (2015) found that while generational transmission alone leads to degeneracy, compositional languages emerge when languages need to be learned as well as used for communication in each generation.

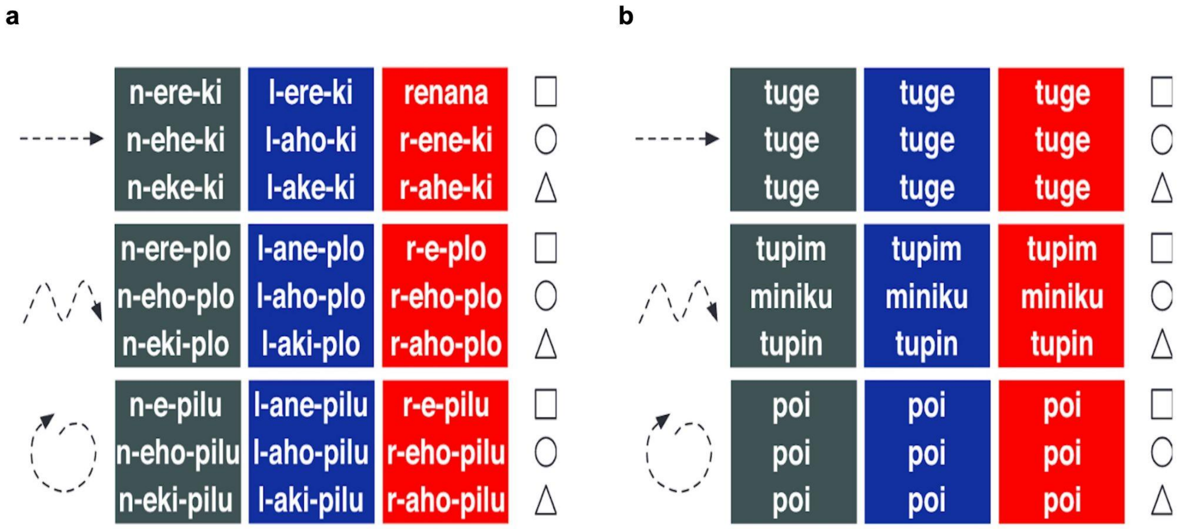

a
n-ere-ki l-ere-ki renana □
n-ehe-ki l-aho-ki r-ene-ki ○
n-eke-ki l-ake-ki r-ahe-ki △
n-ere-plo l-ane-plo r-e-plo □
n-eho-plo l-aho-plo r-eho-plo ○
n-eki-plo l-aki-plo r-aho-plo △
n-e-pilu l-ane-pilu r-e-pilu □
n-eho-pilu l-aho-pilu r-eho-pilu ○
n-eki-pilu l-aki-pilu r-aho-pilu △
b
tuge tuge tuge □
tuge tuge tuge ○
tuge tuge tuge △
tupim tupim tupim □
miniku miniku miniku ○
tupin tupin tupin △
poi poi poi □
poi poi poi ○
poi poi poi △

Figure 2.4. Emerged language structures from different designs of transmission chain experiments. The left side (a) has fallen into degeneracy, but the right side (b) is more systematic, with specific characters assigned to each object element (i.e., movement, color, and shape; figure from Kirby et al., 2008).

These competing pressures for learnability and expressivity have formed a powerful basis to inspire many further experimental studies. Raviv, Meyer, & Lev-Ari (2019) showed that compositional languages can also spontaneously emerge in closed group settings without generational transmission, but where a learnability pressure is nevertheless present through the need to communicate with multiple partners about an expanding meaning space. The studies so far discussed used typed labels and simple scenes, but current research actively studies other signalling modalities, especially gesture (e.g. Motamedi et al., 2019; Schouwstra, Smith, & Kirby, 2020; Fay et al., 2022); but also visual color sequences (Cornish, Smith, & Kirby, 2013), drawings (Fay et al., 2010; Garrod et al., 2010; Theisen-White, Kirby, & Oberlander, 2011), and continuous sounds created using slide whistle (Verhoef, Kirby, & De Boer, 2016) or leap motion (Little, Eryılmaz, & De Boer, 2017) have been studied as signalling devices. Moreover, several studies have explored effects of population structure on language structure and learnability, such as group size (Raviv, Meyer, & Lev-Ari, 2019; Raviv, de Heer Kloots, & Meyer, 2021), network structure (Raviv, Meyer, & Lev-Ari, 2020), and proportion of imperfect or non-native learners (Berdicevskis & Semenuks, 2022), as well as effects of novel communicative environments through virtual reality (Nölle, 2021). Overall, methodologies in the experimental language evolution literature provide promising means to refine theories on how individual level cognitive biases, as well as types of transmission and population structure, shape the structure and learnability of resulting languages.

2.3.2 Music

Historically, laboratory-controlled studies on music evolution began by examining how music changes over time and is being selected by listeners (MacCallum et al., 2012; Salganik et al., 2006; Salganik & Watts, 2008), which operate on methods slightly different from the iterated learning-style transmission chain paradigm. For example, MacCallum et al.'s (2012) "DarwinTunes" experiment isolated the effects of listener selection and random recombination, which were enough to evolve pleasing musical loops from initially random noise over the course of thousands of generations. Later on, the experimental studies in the field of music started adapting the transmission chain experiment paradigm from language research. Ravignani et al. (2016), Jacoby & McDermott (2017), and Lumaca & Baggio (2017) pioneered this line of research almost at the same time.

Ravignani et al. (2016) divided 48 participants into 6 groups (chains). The first participant in each chain had to reproduce, one after the other, 32 randomly-generated drumming patterns to the best of their ability. The resulting patterns were then passed to the next participant in that chain as their input. The drumming patterns of the final generation (i.e. 8th generation) of all 6 chains were not random anymore; they produced distributions of inter-onset intervals (IOIs) with noticeable peaks at specific IOIs, suggesting the emergence of systematicity and learnability. In addition, several widespread musical features (Savage et al., 2015) emerged in the last generation which were not present in the random patterns (Fig. 2.5). Noteworthy, what each chain replicated was not only the universality but also the diversity of rhythm, in that all chains converged to distinct rhythmic patterns while possessing the aforementioned characteristics observable in many musical traditions. Such convergent evolution may have reflected either cognitive constraints such as working memory capacity (Ravignani et al., 2016), information processing capability due to brain functional connectivity (Lumaca et al., 2019), and/or the effect of music-specific abilities like the capacity for isochrony, which is not typical in language and other animals (Fitch, 2017). This paper first showcased the potential of transmission chain experiments in the music domain that recreates music universals, cross-cultural diversity, and human musicality in the lab.

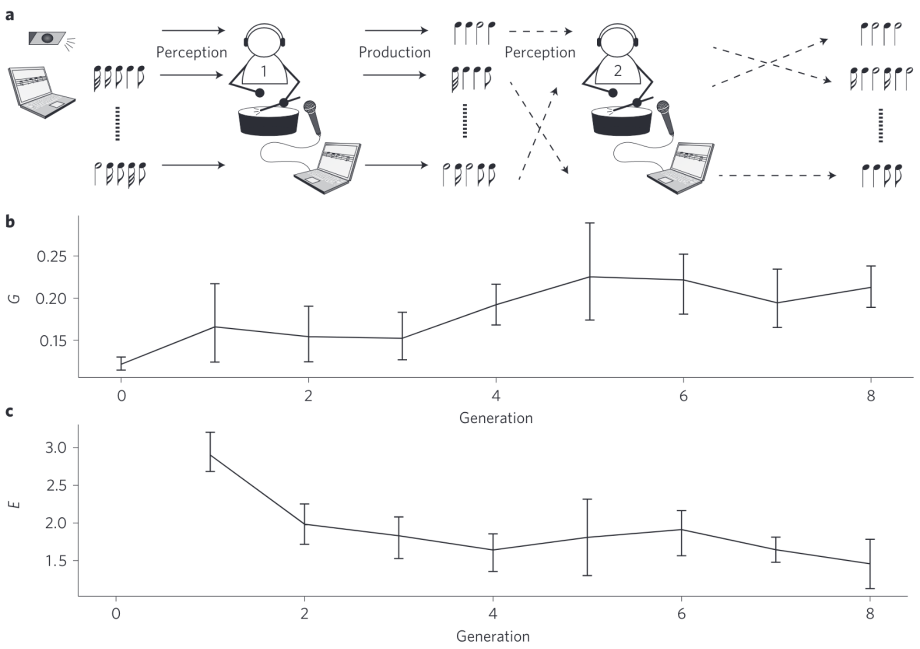


Figure 2.5. A transmission chain experiment showed that rhythmic patterns that were initially randomly generated (a) became more structured as indicated by the structure/systematicity measure G in the panel b (b) and easier to imitate as indicated by the imitation errors E in the panel c (c) over the course of 8 generations (figure from Ravignani et al., 2016).

This line of music transmission experiments has now flourished and expanded to a wide variety of aspects: melody (Anglada-Tort et al., 2022, 2023; Lumaca & Baggio, 2017; Lumaca & Baggio, 2018; Popescu et al., 2022; Shanahan & Albrecht, 2019; Verhoef & Ravignani, 2021), rhythm (Jacoby & McDermott, 2017; Jacoby et al., 2021; Lumaca et al., 2018; Miton et al., 2020; Ravignani et al., 2016; Ravignani et al., 2018), lyrics (deCastro-Arrazola & Kirby, 2019), consonance (Marjieh et al., 2022), vocalization (Ma et al., 2019), and neural mechanisms (Lumaca et al., 2018; 2019; 2021; 2022; 2023). The increasing scale of experiments allows such studies to test multiple factors at high resolution. For example, Anglada-Tort et al. (2023) conducted transmission chain experiments of over 3,000 melodies across almost 2,000 participants from USA and India while manipulating vocal constraints, working memory, cultural exposure, and social interaction, finding that each factor influences the preference of intervals used in melodies. While such laboratory experiments may still be too simple to explain the actual cultural evolution of music in the field, converging evidence from such experimental studies and other approaches (e.g., Savage et al., 2022's observational results), may unveil convincing mechanisms of music evolution.

2.4. Simulation studies

Simulation studies allow researchers to analyze how certain parameters affect evolutionary dynamics (e.g., evolution of language structure conditioned on language learner's bias, Smith et al., 2017) and find out which mathematical models can best explain the observed phenomenon (e.g., frequency of tritones in Western classical music pieces across centuries, Nakamura & Kaneko, 2019). Since cultural evolution is complex, models in simulation studies effectively function as a proof-of-concept; they are abstract descriptions of “what could be possible, and how”, complementing the observational and experimental approaches described above.

Simulation with agent-based models is frequently employed to analyze the dynamics of cultural evolution not just of music and language but also in general (Acerbi et al., 2021; Kandler & Powell, 2018; Kolodny et al., 2015; Mesoudi, 2021). Similar to transmission chain experiments, agent-based models are also used to artificially generate evolutionary dynamics of cultural processes. Transmission chain experiments and agent-based models have a crucial difference: while the former involve complex psychological agents with uncontrollable parameters, the latter involve computational agents who behave according to specific rules and are controlled by a handful of essential parameters.

Simulation studies of music have been less common than of language. Generally speaking, simulation studies build models which reflect specific aspects of the cultural system under study, so the papers reviewed in the subsequent sections may foreground some of the key features of music and language through models tailored for each musical and linguistic evolutionary phenomenon.

2.4.1 Language

Computational simulations of language evolution have made use of a variety of approaches to explore how different kinds of learner biases, communicative interactions, and language properties affect the cultural transmission process and the structural features of emergent languages themselves. A majority of studies center around computational agents which simulate individual language users, though alternative paradigms include evolutionary game theoretic approaches which address more macroscopic population-level quantities, and approaches applying evolutionary computations on grammar formalisms directly without the use of agents (see Grifoni, D'Ulizia, & Ferri, 2015 for an overview). Among agent-based modelling methods, *iterated learning* models and *naming game* models are the two most prominent paradigms. Whereas iterated learning models generally examine how individual-level biases shape languages over generational transmission, naming game models focus more on the interactional dynamics leading to convention formation and shared vocabularies within communities of agents. Bailes & Cuskley (2023) provide a more comprehensive overview of agent-based modelling studies in language evolution. We here briefly highlight some seminal contributions from a particular modelling paradigm known as Bayesian Iterated Learning.

Early iterated learning models were concerned with disentangling properties of languages which could arise from the process of cultural transmission itself from those that needed explanations based on biologically evolved, innate mechanisms. For example, Kirby (2001) demonstrated that compositional structure in language can emerge without natural selection but with cultural transmission of the meaning-signal mapping system between generations of agents. Griffiths & Kalish (2007) formalized the process of iterated learning as an iterative process of Bayesian inference: agents infer hypothesized signal-meaning mappings from observed data, and subsequently use the inferred mappings to produce new data that serves as input for the next iteration. Griffiths & Kalish noted that this process constitutes a Markov chain of conditional distributions (*P*(h|d) and *P*(d|h) in Fig. 2.6), which allowed them to analyze the asymptotic results of the iterated learning process (the final state of data and hypothesis after many iterations). These results revealed that the stationary distribution of the data is determined by the agents' prior distribution over hypotheses, i.e. the outcomes of iterated learning mirror individual agents' internal biases (including e.g. biases for compositional languages). This finding initially suggested that biologically evolved internal biases might be the explanation for linguistic universals (like compositionality) after all. However, later research demonstrated that strong innate constraints are not in fact necessary for cultural universals to emerge (Thompson, Kirby, & Smith, 2016), and the complex relationship between individual-level cognitive biases and population-level linguistic features remains an active area of research.

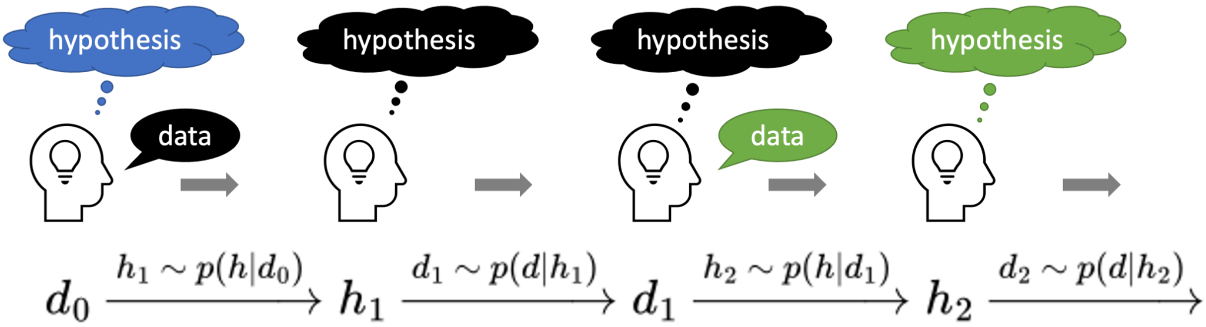

hypothesis
data
hypothesis
hypothesis
data
hypothesis
$d_0 \xrightarrow{h_1 \sim p(h|d_0)} h_1 \xrightarrow{d_1 \sim p(d|h_1)} d_1 \xrightarrow{h_2 \sim p(h|d_1)} h_2 \xrightarrow{d_2 \sim p(d|h_2)}$

Figure 2.6. Overview of iterated learning with Bayesian agents. At each iteration, agents observe new data (d) and update their hypothesis (h) for how data is generated, and subsequently generate new data according to the updated belief (based on Fig. 1 from Griffiths & Kalish, 2007).

Recent studies have dug into explaining the absence and presence of specific linguistic features using simulation. For instance, though combining meaningless elements to create meaningful elements, (“duality of patterning”; Hockett, 1960), has been considered a language universal, Al-Sayyid Bedouin Sign Language (ABSL) is known as an exceptional case with no apparent evidence of the dual patterning structure (Sandler et al., 2011). If such compositional structure can be absent from languages, what conditions are key to the emergence of this feature? Kirby & Tamariz (2022) conducted simulations to answer this question, and demonstrated that the balance between the preference for simplicity and expressivity in the population can shape the combinatoriality structure.

The power of simulation can also be exploited to comparatively study hypothetical scenarios of evolution. Woensdregt et al. (2021) explored how “mindreading” (also known as “theory of mind”) and language have influenced each other. Since language use requires both speakers and listeners to model the mental state of the counterpart to convey and exchange the information, selection pressure on mindreading skills may change the dynamics of the language evolution process. Simulations of language evolution have also included gene-culture coevolution scenarios (Azumagakito et al., 2018). However, simulations of coevolutionary scenarios for music and language have yet to appear. A final emerging trend is the use of powerful deep learning-based algorithms for implementing computational agents, allowing researchers to explore multi-agent simulations with more complex signals and environments than in traditional approaches (see e.g., Chaabouni et al., 2022; Lazaridou & Baroni, 2020). This opens up exciting possibilities for evolutionary simulations in both the linguistic and the musical domain.

2.4.2 Music

Kaplan et al. (2022) developed a model named pPIPPET (Phase Inference from Point Process Event Timing with pattern inference), which imitates the process of entrainment to rhythm patterns based on the prior rhythm template. This model is designed to simulate the process of people's rhythmic perceptions depending on their cultural background, as observed in the cross-cultural transmission chain experiment by Jacoby et al. (2021). Modeling rhythmic behaviors with probabilistic models and simulating the effect of enculturation on rhythm has gained attention from cognitive and psychology music scientists (Cannon, 2021; Sadakata et al., 2006; van der Weij et al., 2017). Although integer-ratio rhythm is widely conserved across many music traditions (Savage et al., 2015), each music has also nurtured unique rhythmic vocabularies which deviate from simple integer-ratio patterns (Clayton, 1996). Unveiling cognitive biases operating on the cultural evolution of music that yield cross-cultural diversity is one of the central questions of the field. Kaplan et al. (2022) approached this by simulating models that learn cultural biases of entrainment. In particular, the prior expectation for specific rhythm patterns (i.e., encultured rhythm patterns) is modeled as a template, and the model performs probabilistic prediction for event occurrence timing in the phase space using the template as the base inhomogeneous point process for event times. The authors' conducted the experiment imitating the procedure of Jacoby et al.'s (2021) experiment with pPIPPET, which produced results consistent with Jacoby et al.'s analysis, indicating that their model potentially captures how convergence to specific rhythm patterns happens conditioned on cultural background. In contrast with Bayesian agent models that repeat sampling data and hypothesis to explore the asymptotic outcome of cultural evolutionary processes as seen in the previous section, their approach focused on learning parameters to configure the model towards targeted cultural rhythm patterns. Such an approach would be particularly more useful to examine culture-specific attractors. However, the choice of priors similarly matters to simulation results, which is the accuracy of entrainment that models can achieve in this case.

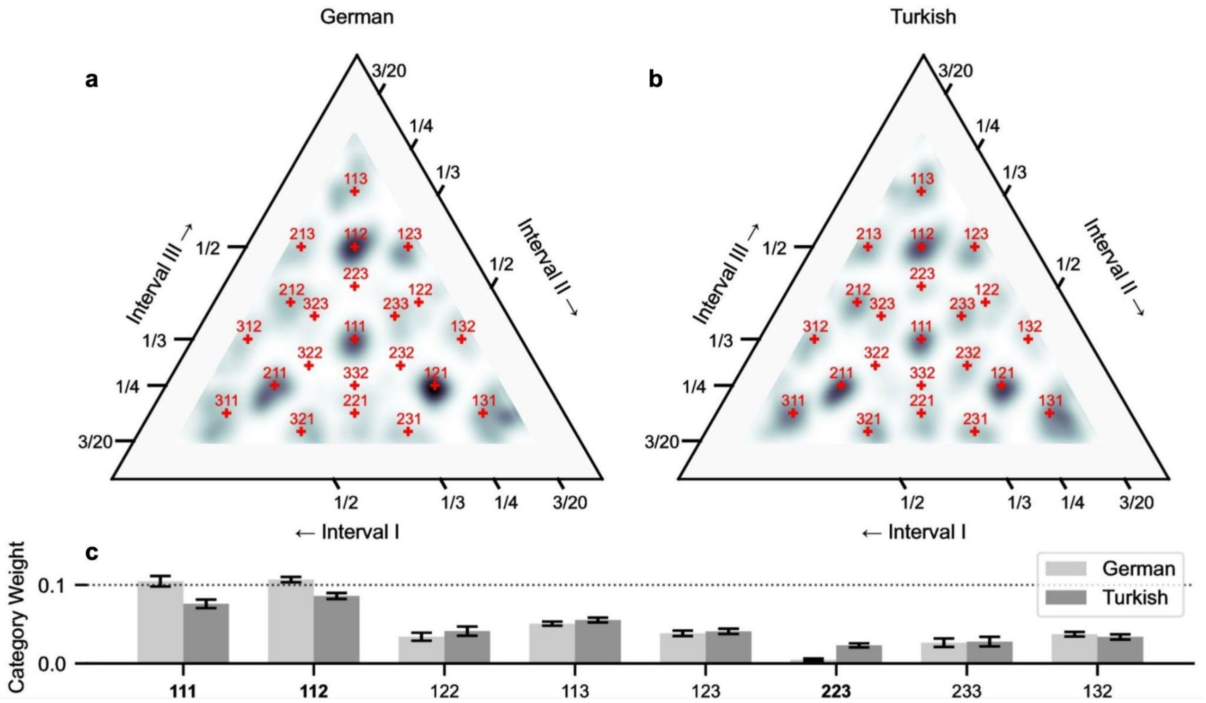


Figure 2.7. Simulation results of pPIPPET demonstrating that the model is capable of imitating the cultural variation of three-interval rhythms shaped by cognitive bias due to transmission and cultural background. Panel a and b show the density (darker areas are more frequent) of the entrainment patterns of three interval rhythms (e.g., 112 means the ratio of the durations of three rhythmic intervals are 1:1:2) by the models trained by German and Turkish music corpus. Panel c shows the estimated ratio of each rhythm category that categories for cyclic permutations are grouped. The patterns of 1:1:1, 1:1:2, and 2:2:3 show differences between the musical traditions, while the other patterns are shared. (figure from Kaplan et al., 2022).

Simulation studies have also been conducted to model the evolution of scales (McBride & Tlusty, 2020), frequencies of acoustic features (Nakamura & Kaneko, 2019; Nakamura, 2021), transmission biases (Youngblood, 2019), the effects of population structure on tune complexity (Street et al., 2022), and the convergence to specific rhythms conditioned on cultural background (Kaplan et al., 2022). Kaplan et al.'s (2022) model reviewed above is actually not an agent-based model, but it demonstrates the potential of formalizing the role of cognitive biases that shape culture-specific traits observed in transmission chain experiments.

2.5. Coevolution of music and language

While the previous sections have described independent work on the cultural evolution of language or of music, this section describes work that directly compares both music and language from an evolutionary framework. We focus on two types of comparisons: 1) *indirect* relationships among musical and linguistic histories, and 2) *direct* relationships between musical and linguistic features.

2.5.1 Indirect relationships among musical and linguistic histories

Reconstruction of language evolution is argued to reflect the history of human populations (e.g., migration, conquest; Cavalli-Sforza et al., 1994; Levinson & Gray, 2012). Meanwhile, music has also been regarded as preserving cultural history (Lomax, 1968). Thus, several attempts have been made to measure the evolutionary relationships between music, language, and human population history.

Brown et al. (2014) assembled musical features of choral songs, languages, and mitochondrial DNA of 9 indigenous populations in Taiwan to analyze correlations among those three types of data. They found significant correlations between music and genes, and between languages and genes. However, similar analyses employing data from northeast Asia (Matsumae et al., 2021) or the Ryukyu archipelago (Nishikawa & Ihara, 2022) did not find a significant correlation between music and genes or linguistic vocabulary and genes, though Matsumae et al. detected a significant correlation between linguistic grammar and genes. When Passmore et al. (2023) conducted a similar analysis on a global scale including 152 societies, music data (song styles) only showed weak relationships with genetic and linguistic similarities. Language demonstrated stronger relationships with genetic histories, although it still displays substantial (~20%) mismatches (Barbieri et al., 2022).

Tree-based models built upon cognates for language evolution assuming primarily vertical transmission have proved useful for understanding cultural evolution, albeit with substantial caveats (c.f., Evans et al., 2021; Neureiter et al., 2022). Similar analyses performed in musical evolution suggest that music may have less tree-like structure and be more independent of population history than language. However, this remains speculative as many studies based on different data sources and regions come to conflicting conclusions (Brown et al., 2014; Bomin et al., 2016; Juhász et al., 2019; Pamjav et al., 2012; Matsumae et al., 2021; Nishikawa & Ihara, 2022) and the only study to directly compare a global sample of music and language found both to contain similar levels of tree-like-ness (delta scores ranging from 0.2~0.4; Passmore et al., 2023).

We emphasize that these comparisons all reflect *indirect* relationships between music/language and genes via shared histories, not direct “genes for music/language”. For discussion of possible direct shared genetic bases of music/language, see Gingras et al. (this volume) and the next section.

2.5.2 Direct relationships between musical and linguistic features

Direct comparison between music and language - particularly in their vocal domain as song and speech - may reveal fundamental similarities and differences that may reflect their coevolution (e.g. Ding et al., 2017; Haiduk & Fitch, 2022; Hansen et al., 2020; Hilton et al., 2022; Vanden Bosch der Nederlanden et al., 2022). For example, Ozaki et al. (2023) analyzed controlled recordings of songs, the same lyrics recited in spoken form, the same melodies in instrumental form, and natural speech recorded by the same speaker/singer representing over 70 global linguistic varieties spanning almost 20 language families (Fig. 2.9). They found that both song and instrumental melodies are consistently higher, slower, and use more stable pitches than speech, while timbral brightness and pitch interval size are consistently similar between song and speech. Albouy et al. (2023) came to similar conclusions after analyzing recordings of 369 speakers/singers from 21 diverse societies, concluding that spectrotemporal modulation consistently distinguish song and speech (e.g., song is slower and uses more energy in the upper harmonics than speech).

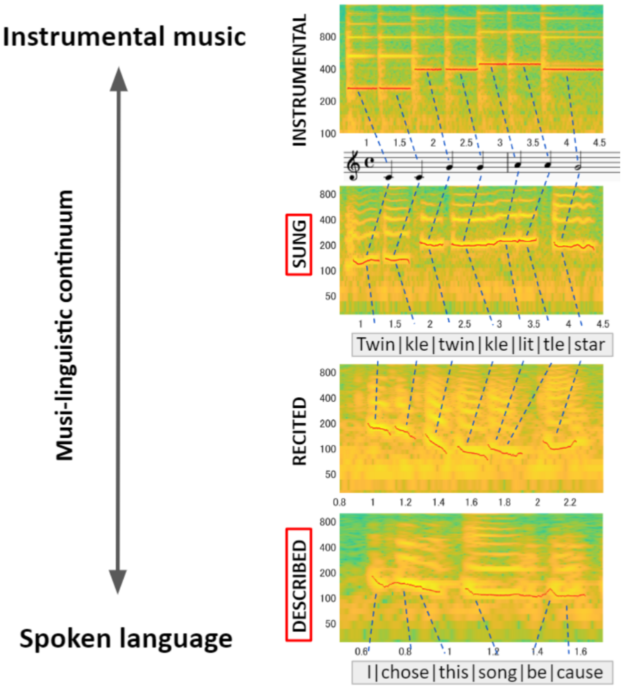


Figure 2.8. Direct comparison of music and language via controlled recordings of the same person (last author PES) capturing a "musi-linguistic continuum" from instrumental music (top) to naturalistic speech (bottom), with song and recited lyrics occupying intermediate positions. (figure from Ozaki et al., 2023).

Such similarities and differences between acoustic features of music and language likely reflect shared and distinct evolutionary mechanisms. For example, the similar interval sizes in speech and music identified by Ozaki et al. (2023) may reflect shared motor constraints on vocalization (Tierney et al., 2011), while the different temporal rates may reflect the need for slower singing to synchronize and bond multiple singers (Savage et al., 2021). Many similarities and differences between music and language may also reflect shared or distinct neural mechanisms. For example, processing rhythm in music or language requires decomposing it into multiple sub-components, such as motor periodicity, beat extraction, audiomotor entrainment, and meter (Kotz et al., 2018). For instance, meter is defined as the grouping of events into a hierarchical structure (e.g., stressed and unstressed musical beats/linguistic syllables). Importantly, these sub-components do not necessarily solely appear in the audio domain (e.g. visual display of rhythmic movement of body parts via dance), which suggests rhythm is essentially multi-modal (Pouw et al., 2021).

Have we evolved any specializations specific to music or language? For example, though music and spoken language both exhibit certain temporal structures, isochronous rhythm is mostly specific to music (Fitch, 2017; Nolan & Jeon, 2014). Cross-species comparative studies may help elucidate evolutionary pathways, and research on songbirds provides a promising hypothesis that rhythm perception is linked to vocal learning capacities (also required for spoken language), and vocal learning was a preadaptation enabling beat perception and synchronization of humans, potentially via gene-culture coevolution (Patel, 2021; Rouse et al., 2021).

2.6. Discussion

Throughout this chapter, we have reviewed the cultural evolution of music, language, and their (co-)evolutionary relationships. In order to expedite more collaborative and integrative research between the two disciplines, we will present future directions that will benefit both fields in this last section.

Cultural evolution of music and language can expand our research methods by borrowing ideas developed in each field. For example, one technique that music researchers can borrow from language evolution is the control of population structure and size. Both population structure and size impact cultural evolution in various ways, including trait complexity, trait diversity, and the rate of evolution (Derex & Mesoudi, 2020). Researchers have already demonstrated that population structure and size can affect the evolution of key features of language (e.g. Berdicevskis & Semenuks, 2022; Raviv et al., 2019). For example, population structure can be understood as some constraints or conditions on the pathway of cultural transmission (e.g., from whom to learn), and Kirby et al.'s simulation (2022) revealed that combinatorial languages emerge much faster when agents learn language from other learners (horizontal transmission) than when agents can only be taught from the oldest agent in the population (vertical transmission). Although observational studies have analyzed how population structure can affect the complexity of folk tunes (Lomax, 1968; Street et al., 2022; Wood et al., 2022), experimental or simulation studies have yet to systematically investigate how population structure influences the cultural evolution of music. The language side might also adopt some approaches emphasized in the cultural evolution of music. For example, language evolution research might benefit from more regularly incorporating internal diversity (e.g., dialects and microvariation among speakers), just as music evolution researchers often incorporate diversity within cultures as well as between them in evolutionary analysis (Rzeszutek et al., 2012).

One unanswered question about the cultural evolution of music and language is how similar cognitive and motor mechanisms constrain the evolution of music and language. For example, memorability or capacity of working memory is supposed to be one of the factors generating regularities in the transmission chain experiments of both music and language (Isbilen & Christiansen, 2020; Ravignani et al., 2016). Experimental results suggest that key features of music and language affect memorability, such as word order (Amici et al., 2019) and pitch discreteness (Haiduk et al., 2020). Ease of vocalization can be counted as another example. Both speech and music are known to converge in similar but distinct ranges of temporal rates across various genres and languages (roughly 1~5Hz for music and 5~10Hz for speech; Ding et al., 2017; Poeppel & Assaneo, 2020; Ozaki et al., 2023; Albouy et al., 2023). This regularity may be attributed to optimization of various factors including limitations on our motor and perceptual capacities for controlling sound sequence production, audio-motor synchronization, and efficient communication of linguistic/musical information. The perception and production of music and language rely on shared cognitive and motor mechanisms to a certain degree, but whether exploited mechanisms operate in the same or different ways may depend on case-by-case (Culbertson & Kirby, 2016). However, revealing similar constraints shaping music and language may inform us how similarities and differences between music and language emerge.

Another stimulating integrative research direction is the need to directly compare music and language together in the same evolutionary studies. Although some of the studies reviewed in section 5 directly compared music and language, most of the studies in Section 2-4 studied only music or only language, but as a result it is difficult to interpret whether their findings were specific to music/language or shared more generally (cf. Singh & Mehr, 2023). Ma et al.'s (2019) transmission chain experiments are an exception that tested whether communicative needs transform a single vocalization into different distinctive types of vocalizations, as illustrated by the proto-music-language hypotheses (Bannan, 2008; Brown, 2000; 2017; this volume; Darwin, 1871; Fenk-Oczlon & Fenk, 2009; Fitch, 2010; Jespersen, 1922; Kirby, 2011; Livingstone, 1973; Ma et al., 2019; Masataka, 2009; Mithen, 2007; Miyagawa et al., 2022; Podlipniak, 2022; Ravignani & de Boer, 2021; Reybrouck & Podlipniak, 2019; Richman, 1987; Thompson et al., 2012). Their experiment showcased that the words used as referential rated as more like speech and the words meant to communicate mental state rated as more like music, which is consistent with the account of the proto-language-music hypothesis. It is important to note that this approach may reflect the biases related to music and language already present in our current cognitive systems but not how music and language evolved based on the cognitive mechanisms that our ancestors had (Ravignani & de Boer, 2021). Nevertheless, experimenting on the cultural evolution of music and language simultaneously is a promising way to obtain integrative insights into specificities and commonalities of music and language.

Music and language are often hypothesized to have co-evolved with broader human cognitive and social aspects such as emotion (Jablonka et al., 2012), mindreading (Woensdregt et al., 2021), and social complexity (Lomax, 1968; Wood et al., 2022). An attempt to analyze how those aspects coevolved with music and language together has not been made yet, but collectively assembling data from music and language can potentially be leveraged for not only human population genetics but also the evolution of human cognitive and social systems.

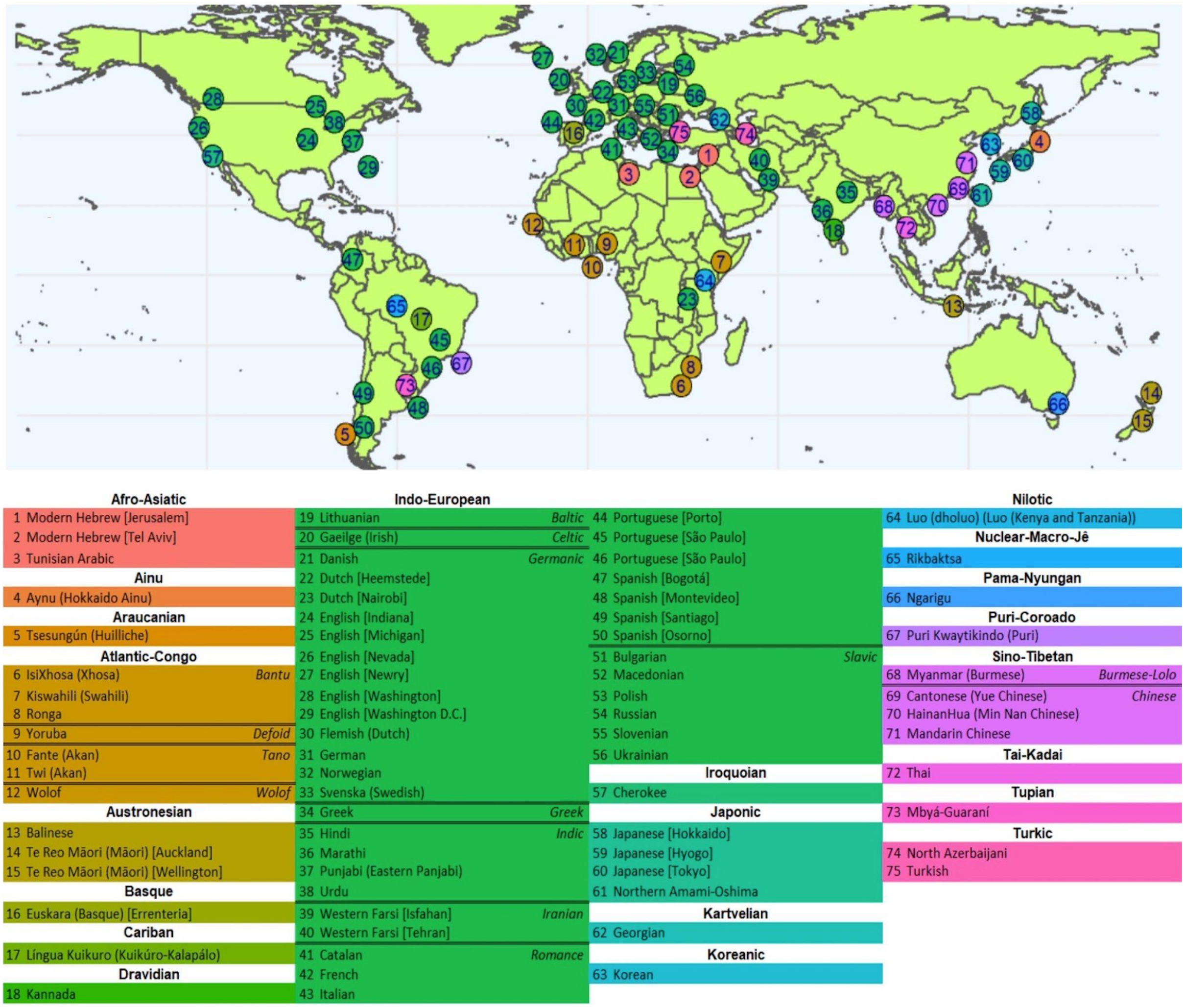
Following the surge of machine learning and artificial intelligence research in recent decades, development of generative models of language and music have shown remarkably human-like qualities in their outputs (Brown et al., 2020; Dhariwal et al., 2020; Oord et al., 2016; Vaswani et al., 2017; Agostinelli et al., 2023). Music and language are still mainly used and produced by humans, but there is a possibility that artificial intelligence technologies may also take part as "generators" that us humans culturally learn music and language from them and these machine learning models get trained by output from us. Novel cultural transmission biases may appear in that scenario, but how these deep generative models will transform the cultural evolution of music and language is still unpredictable. Addressing the role of generative models in the cultural evolution of music and language, including their legal and ethical implications (e.g., in music copyright [Yuan et al., In Press] or algorithmic bias [Noble, 2018]) is a potential emerging research topic.

Mechanisms of the cultural evolution of music and language are very connected to biological evolution. Identifying biological capacities necessary for the perception and production of music (Honing et al., 2015) and language (Haspelmath, 2020), across species (Ghazanfar et al., 2012; Patel et al., 2009) have shed light on their phylogenetic history. In addition, findings about the genetic basis for musical or linguistic abilities (DeSalle & Tattersall, 2018; Niarchou et al., 2022; Tan et al., 2014) and the evolution of vocal organs (Belyk et al., 2021; Blasi et al., 2019; Brown et al., 2021; de Boer, 2019; Fitch et al., 2016) have also been accumulating. Although many studies target either music or language, papers jointly studying music and language have been increasing in volume (Asano, 2022; Belyk et al., 2021; ten Cate & Honing, this volume; Nayak et al., 2022; Kotz et al., 2018; Jarvis, 2019; Patel, 2021; Wesseldijk et al., 2021; Gingras & Drayna, This Volume), which provides an integrative understanding of the evolution of music and language. The biological evolution of music and language both require some general abilities such as vocal learning (Belyk, this volume; Jarvis, 2019; Martins & Boeckx, 2020), which tells us music and language are not merely cultural products observed in only humans but instead have deep evolutionary roots. A holistic view of the evolution of music and language may require incorporating even more evolutionary factors such as the evolution of general cognitive abilities (Kaczanowska et al., 2022), environmental pressures (Bentz et al., 2018; Gavin et al., 2017), and epigenetics (Gokhman et al., 2020).

We need more comprehensive parallel analyses of musical/linguistic evolution that might help shed light on their potential distinct features, evolutionary origins, and/or coevolution (cf. Ozaki et al., 2023 and Passmore et al., 2023). The terms music and language encompass various forms and in some cases the boundary is not obvious (e.g. chanting; Cummins, 2020) or can change depending on context (e.g., the speech-to-song illusion; Deutsch, this volume; Deutsch et al., 2008). Diverse forms of music and language can generate various combinations of communication signals of these two domains. For instance, what can comparison (within and between) vocal music/ spoken language/ instrumental music/ sign language show us about their evolution? What similarities can we find between music and language expressed in the same modality (i.e. vocally, speech and song) vs. across different modalities (e.g. sign or spoken languages and instrumental music)? To what extent are turn-taking or synchronization in speech and musical performances similar or different? What factors control the use of music-like features and speech-like features in people’s utterances and how should we capture the variation of communicative acoustic signals (e.g. the musi-language model (Brown, 2000; Leongómez et al., 2022))?

To address such questions, evolutionary research on music and language must become more inclusive. While evolutionary researchers are beginning to diversify their pool of participants (Apicella et al., 2020), the researchers performing and publishing the research still tend to represent only a small sliver of humanity from English-speaking (Blasi et al., 2022), “WEIRD” (Western, Educated, Industrialized, Rich, Democratic; Henrich et al., 2010) societies, limiting the generalizability and quality of our results. Teaming up with scholars from diverse linguistic and musical backgrounds is critical for this type of research to avoid idiosyncratic biases embedded in a particular language (see Blasi et al., 2022 for the case of

English) and to create a more equitable, inclusive society (Adame et al., 2020; Nature editors, 2022). For example, Ozaki et al. (2023) collaborated with over 70 coauthors representing diverse linguistic varieties throughout the globe (Fig. 2.9), and each coauthor recorded and annotated themselves singing and speaking in different languages. Each coauthor's knowledge of their language, culture, and own intended singing/speaking allowed them to produce segmentations of acoustic units (e.g., syllables/notes) that could not have been achieved by a non-native speaker or an algorithm, resulting in higher quality data and analyses as well as allowing them all to share credit and shape the interpretation of the resulting research paper.



Afro-Asiatic	Indo-European		Nilotic
1 Modern Hebrew [Jerusalem]	19 Lithuanian *Baltic*	44 Portuguese [Porto]	64 Luo (dholuo) (Luo (Kenya and Tanzania))
2 Modern Hebrew [Tel Aviv]	20 Gaeilge (Irish) *Celtic*	45 Portuguese [São Paulo]	**Nuclear-Macro-Jê**
3 Tunisian Arabic	21 Danish *Germanic*	46 Portuguese [São Paulo]	65 Rikbaktsa
Ainu	22 Dutch [Heemstede]	47 Spanish [Bogotá]	**Pama-Nyungan**
4 Aynu (Hokkaido Ainu)	23 Dutch [Nairobi]	48 Spanish [Montevideo]	66 Ngarigu
Araucanian	24 English [Indiana]	49 Spanish [Santiago]	**Puri-Coroado**
5 Tsesungún (Huilliche)	25 English [Michigan]	50 Spanish [Osorno]	67 Puri Kwaytikindo (Puri)
Atlantic-Congo	26 English [Nevada]	51 Bulgarian *Slavic*	**Sino-Tibetan**
6 IsiXhosa (Xhosa) *Bantu*	27 English [Newry]	52 Macedonian	68 Myanmar (Burmese) *Burmese-Lolo*
7 Kiswahili (Swahili)	28 English [Washington]	53 Polish	69 Cantonese (Yue Chinese) *Chinese*
8 Ronga	29 English [Washington D.C.]	54 Russian	70 HainanHua (Min Nan Chinese)
9 Yoruba *Defoid*	30 Flemish (Dutch)	55 Slovenian	71 Mandarin Chinese
10 Fante (Akan) *Tano*	31 German	56 Ukrainian	**Tai-Kadai**
11 Twi (Akan)	32 Norwegian	**Iroquoian**	72 Thai
12 Wolof *Wolof*	33 Svenska (Swedish)	57 Cherokee	**Tupian**
Austronesian	34 Greek *Greek*	**Japonic**	73 Mbyá-Guaraní
13 Balinese	35 Hindi *Indic*	58 Japanese [Hokkaido]	**Turkic**
14 Te Reo Māori (Māori) [Auckland]	36 Marathi	59 Japanese [Hyogo]	74 North Azerbaijani
15 Te Reo Māori (Māori) [Wellington]	37 Punjabi (Eastern Panjabi)	60 Japanese [Tokyo]	75 Turkish
Basque	38 Urdu	61 Northern Amami-Oshima	
16 Euskara (Basque) [Errenteria]	39 Western Farsi [Isfahan] *Iranian*	**Kartvelian**	
Cariban	40 Western Farsi [Tehran]	62 Georgian	
17 Língua Kuikuro (Kuikúro-Kalapálo)	41 Catalan *Romance*	**Koreanic**	
Dravidian	42 French	63 Korean	
18 Kannada	43 Italian		

Figure 2.9. Global collaboration on comparative analysis of music and language facilitates diverse data. Here each circle corresponds to a coauthor who recorded and annotated themselves speaking and singing in their 1st/heritage language. (figure from Ozaki et al., 2023).

2.7. Summary

Music and language are both forms of communication universally observed across human societies, prompting researchers to investigate why and how they evolved. Such research initially focused on the *biological* evolution of the capacities to create and perceive language and music; later work has increasingly tackled the *cultural* evolution approach to study the mechanisms and processes driving the diversity and regularities of music and language. In this chapter, we reviewed seminal studies of the cultural evolution of language and music. We grouped the review into observational studies (e.g., phylogenetic analyses), experimental studies (e.g., transmission chains), simulation studies (e.g., agent-based models), and music-language relationships (e.g., song/speech melody/prosody).

Drawing on the reviews of these four areas of cultural evolutionary studies of music and language, we proposed key ideas that each discipline can learn from the other and promising research topics to encourage collaborative work. In particular, we argued that more direct comparisons of music and language will help to better understand what is shared and distinct about each domain's evolution. This includes similarities and differences in cognitive and motor constraints (e.g., memorability, ease of vocalization), cultural transmission mechanisms (e.g., vertical/horizontal transmission with/independent from human populations), and underlying biological bases (e.g., vocal learning).

Much remains to be done for comprehensive parallel analyses of the cultural evolution of music and language. The extent to which music, language, and genes have co-evolved still remains elusive. However, increasing our knowledge of cultural evolution and both globally and locally evolved cultural traits of music and language may identify constraints on what necessary biological and cognitive bases underly musical and linguistic evolution. The advancement of integrative research of these two disciplines will shed light not only on the cultural evolution of music and language but also their biological evolution and potential coevolution.

Acknowledgments:
We thank Daniela Sammler for feedback, Simon Kirby and Dan Dediu for early discussion of ideas for this chapter and Matthew Scarborough, Simon Greenhill, Michael Dunn, and Samopriya Basu for advice on cognate examples in Fig. 2.2. We thank Simon Kirby and Tom Griffiths for advice on adapting figures from Kirby et al. (2008) and Griffiths & Kalish (2007), and Quentin Atkinson for providing data to recreate the Indo-European phylogeny from Bouckaert et al. (2012). Figure from Ravignani et al. (2016) is reproduced under the Nature-Springer guideline allowing authors "To reuse figures or tables created by the Author and contained in the Contribution in oral presentations and other works created by them." (https://www.nature.com/nature-portfolio/reprints-and-permissions/permissions-requests). Other figures are reprinted according to their original CC BY licenses.

YO is supported by the Japan Science and Technology Agency (Grant Number JPMJSP2123 of Support for Pioneering Research Initiated by the Next Generation). PES is supported by funding from the New Zealand Government, administered by the Royal Society Te Apārangi (Rutherford Discovery Fellowship 22-UOA-040 and Marsden Fast-Start Grant 22-UOA-052), and by the Japanese Government, administered by the Japan Society for the Promotion of Science (KAKENHI Grant-in-Aid #19KK0064). MdHK is funded by the Netherlands Organization for Scientific Research (NWO), through a Gravitation Grant 024.001.006 to the Language in Interaction Consortium. Center for Music in the Brain is funded by the Danish National Research Foundation (DNRF117). The Comparative Bioacoustics Group is funded by Max Planck Group Leader funding to A.R.

Author contributions:

-Conceived the project: Savage, Ravignani
-Outline brainstorming: Ozaki, Savage, Ravignani, de Heer Kloots
-Drafting initial manuscript: Ozaki
-Editing/rewriting manuscript: Savage, de Heer Kloots, Ravignani

References

Aboitiz, F. (2018). A Brain for Speech. Evolutionary Continuity in Primate and Human Auditory-Vocal Processing. *Frontiers in Neuroscience*, *12*. https://www.frontiersin.org/articles/10.3389/fnins.2018.00174

Acerbi, A., Charbonneau, M., Miton, H., & Scott-Phillips, T. (2021). Culture without copying or selection. *Evolutionary Human Sciences*, *3*, e50. https://doi.org/10.1017/ehs.2021.47

Adame, F. (2021). Meaningful collaborations can end 'helicopter research.' *Nature*. https://doi.org/10.1038/d41586-021-01795-1

Agostinelli, A., Denk, T. I., Borsos, Z., Engel, J., Verzetti, M., Caillon, A., Huang, Q., Jansen, A., Roberts, A., Tagliasacchi, M., Sharifi, M., Zeghidour, N., & Frank, C. (2023). MusicLM: Generating Music From Text. *ArXiv* preprint: https://doi.org/10.48550/arXiv.2301.11325

Alaica, A. K., González La Rosa, L. M., Yépez Álvarez, W., & Jennings, J. (2022). The day the music died: Making and playing bone wind instruments at La Real in Middle Horizon, Peru (600–1000 CE). *Journal of Anthropological Archaeology*, *68*, 101459. https://doi.org/10.1016/j.jaa.2022.101459

Albouy, P., Mehr, S. A., Hoyer, R. S., Ginzburg, J., & Zatorre, R. J. (2023). *Spectro-temporal acoustical markers differentiate speech from song across cultures*. bioRxiv Preprint. https://doi.org/10.1101/2023.01.29.526133

Amici, F., Sánchez-Amaro, A., Sebastián-Enesco, C., Cacchione, T., Allritz, M., Salazar-Bonet, J., & Rossano, F. (2019). The word order of languages predicts native speakers' working memory. *Scientific Reports*, *9*(1), Article 1. https://doi.org/10.1038/s41598-018-37654-9

Anglada-Tort, M., Harrison, P. M. C., & Jacoby, N. (2022). Studying the Effect of Oral Transmission on Melodic Structure using Online Iterated Singing Experiments. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *44*(44). https://escholarship.org/uc/item/3567q2vf

Anglada-Tort, M., Harrison, P. M. C., Lee, H., & Jacoby, N. (2023). Large-scale iterated singing experiments reveal oral transmission mechanisms underlying music evolution. *Current Biology*, *0*(0). https://doi.org/10.1016/j.cub.2023.02.070

Apicella, C., Norenzayan, A., & Henrich, J. (2020). Beyond WEIRD: A review of the last decade and a look ahead to the global laboratory of the future. *Evolution and Human Behavior*, *41*(5), 319–329. https://doi.org/10.1016/j.evolhumbehav.2020.07.015

Asano, R. (2022). The evolution of hierarchical structure building capacity for language and music: A bottom-up perspective. *Primates*, *63*(5), 417–428. https://doi.org/10.1007/s10329-021-00905-x

Atkinson, Q. D., & Gray, R. D. (2005). Curious Parallels and Curious Connections—Phylogenetic Thinking in Biology and Historical Linguistics. *Systematic Biology*, *54*(4), 513–526. https://doi.org/10.1080/10635150590950317

Azumagakito, T., Suzuki, R., & Arita, T. (2018). An integrated model of gene-culture coevolution of language mediated by phenotypic plasticity. *Scientific Reports*, *8*(1), Article 1. https://doi.org/10.1038/s41598-018-26233-7

Bailes, R., & Cuskley, C. (2023). The cultural evolution of language. In J. J. Tehrani, J. Kendal, & R. Kendal (Eds.), *The Oxford Handbook of Cultural Evolution* (p. C59P1-C59S14). Oxford University Press. . https://doi.org/10.1093/oxfordhb/9780198869252.013.59

Bannan, N. (2008). Language out of Music: The Four Dimensions of Vocal Learning. *The Australian Journal of Anthropology*, *19*(3), 272–293. https://doi.org/10.1111/j.1835-9310.2008.tb00354.x

Barbieri, C., Blasi, D. E., Arango-Isaza, E., Sotiropoulos, A. G., Hammarström, H., Wichmann, S., Greenhill, S. J., Gray, R. D., Forkel, R., Bickel, B., & Shimizu, K. K. (2022). A global analysis of matches and mismatches between human genetic and linguistic histories. *Proceedings of the National Academy of Sciences*, *119*(47), e2122084119. https://doi.org/10.1073/pnas.2122084119

Barham, L., & Everett, D. (2021). Semiotics and the Origin of Language in the Lower Palaeolithic. *Journal of Archaeological Method and Theory*, *28*(2), 535–579. https://doi.org/10.1007/s10816-020-09480-9

Bartlett, F. C. (1932). *Remembering: A study in experimental and social psychology*. Cambridge University Press.

Bayard, S. P. (1954). Two representative tune families of British tradition. *Midwest Folklore*, 4(1), 13–33.

Belyk, M., Eichert, N., & McGettigan, C. (2021). A dual larynx motor networks hypothesis. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1840), 20200392. https://doi.org/10.1098/rstb.2020.0392

Belyk, M., Brown, R., Beal, D. S., Roebroeck, A., McGettigan, C., Guldner, S., & Kotz, S. A. (2021). Human larynx motor cortices coordinate respiration for vocal-motor control. *NeuroImage*, *239*, 118326. https://doi.org/10.1016/j.neuroimage.2021.118326

Bentz, C., & Winter, B. (2013). Languages with more second language learners tend to lose nominal case. *Language Dynamics and Change,* *3*(1), 1-27. https://doi.org/10.1163/22105832-13030105

Bentz, C., Dediu, D., Verkerk, A., & Jäger, G. (2018). The evolution of language families is shaped by the environment beyond neutral drift. *Nature Human Behaviour*, *2*(11), Article 11. https://doi.org/10.1038/s41562-018-0457-6

Berdicevskis, A., & Semenuks, A. (2022). Imperfect language learning reduces morphological overspecification: Experimental evidence. *PLOS ONE*, *17*(1), e0262876. https://doi.org/10.1371/journal.pone.0262876

Belyk, M. (in press). Voice-motor control. In *The Oxford Handbook of Language and Music*. Oxford University Press.

Blasi, D. E., Moran, S., Moisik, S. R., Widmer, P., Dediu, D., & Bickel, B. (2019). Human sound systems are shaped by post-Neolithic changes in bite configuration. *Science*, *363*(6432), eaav3218. https://doi.org/10.1126/science.aav3218

Blasi, D. E., Henrich, J., Adamou, E., Kemmerer, D., & Majid, A. (2022). Over-reliance on English hinders cognitive science. *Trends in Cognitive Sciences*, *0*(0). https://doi.org/10.1016/j.tics.2022.09.015

Boilès, C. L. (1973). Reconstruction of proto-melody. *Anu. Interam. Investig. Music*. 9, 45–63. 110.

Bomin, S. L., Lecointre, G., & Heyer, E. (2016). The Evolution of Musical Diversity: The Key Role of Vertical Transmission. *PLOS ONE*, *11*(3), e0151570. https://doi.org/10.1371/journal.pone.0151570

Bouckaert, R., Lemey, P., Dunn, M., Greenhill, S. J., Alekseyenko, A. V., Drummond, A. J., Gray, R. D., Suchard, M. A., & Atkinson, Q. D. (2012). Mapping the Origins and Expansion of the Indo-European Language Family. *Science*, *337*(6097), 957–960. https://doi.org/10.1126/science.1219669

Boyd, R., & Henrich, J. (2002). On Modeling Cognition and Culture: Why cultural evolution does not require replication of representations. *Journal of Cognition and Culture*, *2*(2), 87–112. https://doi.org/10.1163/156853702320281836

Bronson, B. H. (1969). *The Ballad as Song*. University of California Press.

Brown, D. E. (1991). *Human Universals*. McGraw-Hill.

Brown, S. (2000). The "Musilanguage" model of music evolution. In S. Brown, B. Merker, & N. L. Wallin (Eds.), *The origins of music*. MIT Press.

Brown, S. (2017). A Joint Prosodic Origin of Language and Music. *Frontiers in Psychology*, *8*. https://www.frontiersin.org/articles/10.3389/fpsyg.2017.01894

Brown, S. (in press). Protomusic & Protolanguage. In *The Oxford Handbook of Language and Music*. Oxford University Press.

Brown, S., Savage, P. E., Ko, A. M.-S., Stoneking, M., Ko, Y.-C., Loo, J.-H., & Trejaut, J. A. (2014). Correlations in the population structure of music, genes and language. *Proceedings of the Royal Society B: Biological Sciences*, *281*(1774), 20132072. https://doi.org/10.1098/rspb.2013.2072

Brown, S., Yuan, Y., & Belyk, M. (2021). Evolution of the speech-ready brain: The voice/jaw connection in the human motor cortex. *Journal of Comparative Neurology*, *529*(5), 1018–1028. https://doi.org/10.1002/cne.24997

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., … Amodei, D. (2020). Language Models are Few-Shot Learners. *Advances in Neural Information Processing Systems*, *33*, 1877–1901. https://proceedings.neurips.cc/paper/2020/hash/1457c0d6bfcb4967418bfb8ac142f64a-Abstract.html

Bryden, J., Wright, S. P., & Jansen, V. A. A. (2018). How humans transmit language: Horizontal transmission matches word frequencies among peers on Twitter. *Journal* *of The Royal Society Interface*, *15*(139), 20170738. https://doi.org/10.1098/rsif.2017.0738

Cannon, J. (2021). Expectancy-based rhythmic entrainment as continuous Bayesian inference. *PLOS Computational Biology*, *17*(6), e1009025. https://doi.org/10.1371/journal.pcbi.1009025

Cavalli-Sforza, L. L., Menozzi, P., & Piazza, A. (1994). *The history and geography of human genes*. Princeton University Press.

Chaabouni, R., Strub, F., Altché, F., Tarassov, E., Tallec, C., Davoodi, E., Mathewson, K.W., Tieleman, O., & Piot, B. (2022). Emergent communication at scale. In *International Conference on Learning Representations (ICLR)*. https://openreview.net/forum?id=AUGBfDIV9rL

Cherbuliez, A. E., Alvarenga, O., Karpeles, M., Kennedy, D., Kraus, E., Kunst, J., & Lange, C. (1955). Definition of folk music. *Journal of the International Folk Music Council*, 7, 23. https://doi.org/10.1017/S0950792200016537

Christiansen, M. H., & Kirby, S. (Eds.). (2003). *Language evolution*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199244843.001.0001

Claidière, N., & Sperber, D. (2007). The role of attraction in cultural evolution. *Journal of Cognition and Culture*, *7*(1–2), 89–111. https://doi.org/10.1163/156853707X171829

Clayton, M. R. L. (1996). Free Rhythm: Ethnomusicology and the Study of Music without Metre. *Bulletin of the School of Oriental and African Studies, University of London*, *59*(2), 323–332.

Cornish, H., Smith, K., & Kirby, S. (2013). Systems from Sequences: An Iterated Learning Account of the Emergence of Systematic Structure in a Non-Linguistic Task. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *35*(35). https://escholarship.org/uc/item/005080vf

Creanza, N., Kolodny, O., & Feldman, M. W. (2017). Cultural evolutionary theory: How culture evolves and why it matters. *Proceedings of the National Academy of Sciences*, *114*(30), 7782–7789. https://doi.org/10.1073/pnas.1620732114

Culbertson, J., & Kirby, S. (2016). Simplicity and specificity in language: Domain-general biases have domain-specific effects. *Frontiers in psychology, 6*, 1964. https://doi.org/10.3389/fpsyg.2015.01964

Cummins, F. (2020). The territory between speech and song: A joint speech perspective. *Music Perception, 37*(4), 347-358.

Darwin, C. (1871). *The descent of man*. Watts & Co.

deCastro-Arrazola, V., & Kirby, S. (2019). The emergence of verse templates through iterated learning. *Journal of Language Evolution*, *4*(1), 28–43. https://doi.org/10.1093/jole/lzy013

de Boer, B. (2019). Evolution of Speech: Anatomy and Control. *Journal of Speech, Language, and Hearing Research*, *62*(8S), 2932–2945. https://doi.org/10.1044/2019_JSLHR-S-CSMC7-18-0293

Dediu, D. (2011). Are Languages Really Independent from Genes? If Not, What Would a Genetic Bias Affecting Language Diversity Look Like? *Human Biology*, *83*(2), 279–296. https://doi.org/10.3378/027.083.0208

Derex, M., & Mesoudi, A. (2020). Cumulative Cultural Evolution within Evolving Population Structures. *Trends in Cognitive Sciences*, *24*(8), 654–667. https://doi.org/10.1016/j.tics.2020.04.005

DeSalle, R., & Tattersall, I. (2018). What aDNA can (and cannot) tell us about the emergence of language and speech. *Journal of Language Evolution*, *3*(1), 59–66. https://doi.org/10.1093/jole/lzx018

Deutsch, D. (in press). Speech-to-Song Illusion. In *The Oxford Handbook of Language and Music*. Oxford University Press.

Deutsch, D., Lapidis, R., & Henthorn, T. (2008). The speech‐to‐song illusion. *The Journal of the Acoustical Society of America*, *124*, 2471–2471. https://doi.org/10.1121/1.4808987

Dhariwal, P., Jun, H., Payne, C., Kim, J. W., Radford, A., & Sutskever, I. (2020). *Jukebox: A Generative Model for Music* (arXiv:2005.00341). arXiv. https://doi.org/10.48550/arXiv.2005.00341

Ding, N., Patel, A. D., Chen, L., Butler, H., Luo, C., & Poeppel, D. (2017). Temporal modulations in speech and music. *Neuroscience & Biobehavioral Reviews*, *81*, 181–187. https://doi.org/10.1016/j.neubiorev.2017.02.011

Ergin, R. (2022). Emerging Lexicon for Objects in Central Taurus Sign Language. *Languages, 7*(2), 118. https://doi.org/10.3390/languages7020118

Evans, C. L., Greenhill, S. J., Watts, J., List, J.-M., Botero, C. A., Gray, R. D., & Kirby, K. R. (2021). The uses and abuses of tree thinking in cultural evolution. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1828), 20200056. https://doi.org/10.1098/rstb.2020.0056

d'Errico, F., Henshilwood, C., Lawson, G., Vanhaeren, M., Tillier, A.-M., Soressi, M., Bresson, F., Maureille, B., Nowell, A., Lakarra, J., Backwell, L., & Julien, M. (2003). Archaeological Evidence for the Emergence of Language, Symbolism, and Music–An Alternative Multidisciplinary Perspective. *Journal of World Prehistory*, *17*(1), 1–70. https://doi.org/10.1023/A:1023980201043

Fay, N., Garrod, S., Roberts, L., & Swoboda, N. (2010). The Interactive Evolution of Human Communication Systems. *Cognitive Science*, *34*(3), 351–386. https://doi.org/10.1111/j.1551-6709.2009.01090.x

Fay, N., Walker, B., Ellison, T. M., Blundell, Z., De Kleine, N., Garde, M., Lister, C. J., & Goldin-Meadow, S. (2022). Gesture is the primary modality for language creation. *Proceedings of the Royal Society B: Biological Sciences*, *289*(1970), 20220066. https://doi.org/10.1098/rspb.2022.0066

Feldman, M. W., & Laland, K. N. (1996). Gene-culture coevolutionary theory. *Trends in Ecology & Evolution*, *11*(11), 453–457. https://doi.org/10.1016/0169-5347(96)10052-5

Fenk-Oczlon, G., & Fenk, A. (2009). Some parallels between language and music from a cognitive and evolutionary perspective. *Musicae Scientiae*, *13*(2_suppl), 201–226. https://doi.org/10.1177/1029864909013002101

Fitch, W. T. (2010). *The Evolution of Language*. Cambridge University Press. https://doi.org/10.1017/CBO9780511817779

Fitch, W. T. (2017). Cultural evolution: Lab-cultured musical universals. *Nature Human Behaviour*, *1*(1), Article 1. https://doi.org/10.1038/s41562-016-0018

Fitch, W. T. (in press). Comparative Biology. In *The Oxford Handbook of Language and Music*. Oxford University Press.

Galantucci, B. (2005). An Experimental Study of the Emergence of Human Communication Systems. *Cognitive Science, 29*(5), 737–767. https://doi.org/10.1207/s15516709cog0000_34

Galantucci, B., & Garrod, S. (2011). Experimental Semiotics: A Review. *Frontiers in Human Neuroscience, 5*. https://doi.org/10.3389/fnhum.2011.00011

Garrod, S., Fay, N., Lee, J., Oberlander, J., & MacLeod, T. (2010). Foundations of Representation: Where Might Graphical Symbol Systems Come From? *Cognitive Science*, *31*(6), 961–987. https://doi.org/10.1080/03640210701703659

Gavin, M. C., Rangel, T. F., Bowern, C., Colwell, R. K., Kirby, K. R., Botero, C. A., Dunn, M., Dunn, R. R., McCarter, J., Pacheco Coelho, M. T., & Gray, R. D. (2017). Process-based modelling shows how climate and demography shape language diversity. *Global Ecology and Biogeography*, *26*(5), 584–591. https://doi.org/10.1111/geb.12563

Gell-Mann, M., & Ruhlen, M. (2011). The origin and evolution of word order. *Proceedings of the National Academy of Sciences*, *108*(42), 17290–17295. https://doi.org/10.1073/pnas.1113716108

Ghazanfar, A. A., Takahashi, D. Y., Mathur, N., & Fitch, W. T. (2012). Cineradiography of Monkey Lip-Smacking Reveals Putative Precursors of Speech Dynamics. *Current Biology*, *22*(13), 1176–1182. https://doi.org/10.1016/j.cub.2012.04.055

Gingras, B., & Drayna, D. (in press). Genetics of speech, language, and music. In *The Oxford Handbook of Language and Music*. Oxford University Press.

Gokhman, D., Nissim-Rafinia, M., Agranat-Tamir, L., Housman, G., García-Pérez, R., Lizano, E., Cheronet, O., Mallick, S., Nieves-Colón, M. A., Li, H., Alpaslan-Roodenberg, S., Novak, M., Gu, H., Osinski, J. M., Ferrando-Bernal, M., Gelabert, P., Lipende, I., Mjungu, D., Kondova, I., … Carmel, L. (2020). Differential DNA methylation of vocal and facial anatomy genes in modern humans. *Nature Communications*, *11*(1), Article 1. https://doi.org/10.1038/s41467-020-15020-6

Gray, R. D., & Atkinson, Q. D. (2003). Language-tree divergence times support the Anatolian theory of Indo-European origin. *Nature*, *426*(6965), Article 6965. https://doi.org/10.1038/nature02029

Gray, R. D., Drummond, A. J., & Greenhill, S. J. (2009). Language Phylogenies Reveal Expansion Pulses and Pauses in Pacific Settlement. *Science*, *323*(5913), 479–483. https://doi.org/10.1126/science.1166858

Greenhill, S. (in press). Language phylogenies: modelling the evolution of language. In *The Oxford Handbook of Cultural Evolution*. Oxford University Press.

Greenhill, S. J., Wu, C.-H., Hua, X., Dunn, M., Levinson, S. C., & Gray, R. D. (2017). Evolutionary dynamics of language systems. *Proceedings of the National Academy of Sciences*, *114*(42), E8822–E8829. https://doi.org/10.1073/pnas.1700388114

Griffiths, T. L., & Kalish, M. L. (2007). Language Evolution by Iterated Learning With Bayesian Agents. *Cognitive Science*, *31*(3), 441–480. https://doi.org/10.1080/15326900701326576

Grifoni, P., D'Ulizia, A., & Ferri, F. (2016). Computational methods and grammars in language evolution: a survey. *Artificial Intelligence Review, 45*, 369-403. https://doi.org/10.1007/s10462-015-9449-3

Hahn, M., & Xu, Y. (2022). Crosslinguistic word order variation reflects evolutionary pressures of dependency and information locality. *Proceedings of the National Academy of Sciences*, *119*(24), e2122604119. https://doi.org/10.1073/pnas.2122604119

Haiduk, F., & Fitch, W. T. (2022). Understanding Design Features of Music and Language: The Choric/Dialogic Distinction. *Frontiers in Psychology*, *13*. https://www.frontiersin.org/article/10.3389/fpsyg.2022.786899

Haiduk, F., Quigley, C., & Fitch, W. T. (2020). Song Is More Memorable Than Speech Prosody: Discrete Pitches Aid Auditory Working Memory. *Frontiers in Psychology*, *11*, 3493. https://doi.org/10.3389/fpsyg.2020.586723

Hansen, J. H. L., Bokshi, M., & Khorram, S. (2020). Speech variability: A cross-language study on acoustic variations of speaking versus untrained singing. *The Journal of the Acoustical Society of America*, *148*(2), 829. https://doi.org/10.1121/10.0001526

Haspelmath, M. (2020). Human Linguisticality and the Building Blocks of Languages. *Frontiers in Psychology*, *10*. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.03056

Hauser, M. D., Chomsky, N., & Fitch, W. T. (2002). The Faculty of Language: What Is It, Who Has It, and How Did It Evolve? *Science*, *298*(5598), 1569–1579. https://doi.org/10.1126/science.298.5598.1569

Hay, J., & Bauer, L. (2007). Phoneme inventory size and population size. *Language, 83*(2), 388-400. https://doi.org/10.1353/lan.2007.0071

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences*, *33*(2–3), 61–83. https://doi.org/10.1017/S0140525X0999152X

Hilton, C. B., Moser, C. J., Bertolo, M., Lee-Rubin, H., Amir, D., Bainbridge, C. M., Simson, J., Knox, D., Glowacki, L., Alemu, E., Galbarczyk, A., Jasienska, G., Ross, C. T., Neff, M. B., Martin, A., Cirelli, L. K., Trehub, S. E., Song, J., Kim, M., … Mehr, S. A. (2022). Acoustic regularities in infant-directed speech and song across cultures. *Nature Human Behaviour*, *6*(11), Article 11. https://doi.org/10.1038/s41562-022-01410-x

Hockett, C. F. (1960). The Origin of Speech. *Scientific American*, *203*(3), 88–97.

Hoeschele, M., & Fitch, W. T. (2022). Cultural evolution: Conserved patterns of melodic evolution across musical cultures. *Current Biology*, *32*(6), R265–R267. https://doi.org/10.1016/j.cub.2022.01.080

Honing, H., ten Cate, C., Peretz, I., & Trehub, S. E. (2015). Without it no music: Cognition, biology and evolution of musicality. *Philosophical Transactions of the*

Royal Society B: Biological Sciences, *370*(1664), 20140088. https://doi.org/10.1098/rstb.2014.0088

Hruschka, D. J., Branford, S., Smith, E. D., Wilkins, J., Meade, A., Pagel, M., & Bhattacharya, T. (2015). Detecting Regular Sound Changes in Linguistics as Events of Concerted Evolution. *Current Biology*, *25*(1), 1–9. https://doi.org/10.1016/j.cub.2014.10.064

Isbilen, E. S., & Christiansen, M. H. (2020). Chunk-Based Memory Constraints on the Cultural Evolution of Language. *Topics in Cognitive Science*, *12*(2), 713–726. https://doi.org/10.1111/tops.12376

Jablonka, E., Ginsburg, S., & Dor, D. (2012). The co-evolution of language and emotions. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *367*(1599), 2152–2159. https://doi.org/10.1098/rstb.2012.0117

Jacoby, N., & McDermott, J. H. (2017). Integer Ratio Priors on Musical Rhythm Revealed Cross-culturally by Iterated Reproduction. *Current Biology*, *27*(3), 359–370. https://doi.org/10.1016/j.cub.2016.12.031

Jacoby, N., Polak, R., Grahn, J., Cameron, D. J., Lee, K. M., Godoy, R., Undurraga, E. A., Huanca, T., Thalwitzer, T., Doumbia, N., Goldberg, D., Margulis, E., Wong, P. C. M., Jure, L., Rocamora, M., Fujii, S., Savage, P. E., Ajimi, J., Konno, R., … McDermott, J. H. (2021). *Universality and cross-cultural variation in mental representations of music revealed by global comparison of rhythm priors*. PsyArXiv. https://doi.org/10.31234/osf.io/b879v

Jarvis, E. D. (2019). Evolution of vocal learning and spoken language. *Science*, *366*(6461), 50–54. https://doi.org/10.1126/science.aax0287

Jespersen, O. (1922). *Language: Its Nature, Development, and Origin*. Routledge. https://doi.org/10.4324/9780203715895

Josserand, M., Meeussen, E., Majid, A., & Dediu, D. (2021). Environment and culture shape both the colour lexicon and the genetics of colour perception. *Scientific Reports*, *11*(1), Article 1. https://doi.org/10.1038/s41598-021-98550-3

Juhász, Z., Dudás, E., Vágó-Zalán, A., & Pamjav, H. (2019). A simultaneous search for footprints of early human migration processes using the genetic and folk music data in Eurasia. *Molecular Genetics and Genomics*, *294*(4), 941–962. https://doi.org/10.1007/s00438-019-01539-x

Kaczanowska, J., Ganglberger, F., Chernomor, O., Kargl, D., Galik, B., Hess, A., Moodley, Y., von Haeseler, A., Bühler, K., & Haubensak, W. (2022). Molecular archaeology of human cognitive traits. *Cell Reports*, *40*(9), 111287. https://doi.org/10.1016/j.celrep.2022.111287

Kandler, A., & Powell, A. (2018). Generative inference for cultural evolution. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1743), 20170056. https://doi.org/10.1098/rstb.2017.0056

Kaplan, T., Cannon, J., Jamone, L., & Pearce, M. (2022). Modeling enculturated bias in entrainment to rhythmic patterns. *PLOS Computational Biology*, *18*(9), e1010579. https://doi.org/10.1371/journal.pcbi.1010579

Kim, Y., & Morin, O. (2023). Literate culture and cognition. In J. J. Tehrani, J. Kendal, & R. Kendal (Eds.), *The Oxford Handbook of Cultural Evolution* (p.

C63S1-C63S7). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780198869252.013.63

Kimura, M. (1983). *The Neutral Theory of Molecular Evolution*. Cambridge University Press.

Kirby, S. (2001). Spontaneous evolution of linguistic structure-an iterated learning model of the emergence of regularity and irregularity. *IEEE Transactions on Evolutionary Computation*, *5*(2), 102–110. https://doi.org/10.1109/4235.918430

Kirby, S. (2011). Darwin's musical protolanguage: An increasingly compelling picture. In P. Rebuschat, M. Rohmeier, J. A. Hawkins, & I. Cross (Eds.), *Language and Music as Cognitive Systems*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199553426.003.0010

Kirby, S., & Tamariz, M. (2022). Cumulative cultural evolution, population structure and the origin of combinatoriality in human language. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *377*(1843), 20200319. https://doi.org/10.1098/rstb.2020.0319

Kirby, S., Cornish, H., & Smith, K. (2008). Cumulative cultural evolution in the laboratory: An experimental approach to the origins of structure in human language. *Proceedings of the National Academy of Sciences*, *105*(31), 10681–10686. https://doi.org/10.1073/pnas.0707835105

Kirby, S., Griffiths, T., & Smith, K. (2014). Iterated learning and the evolution of language. *Current Opinion in Neurobiology*, *28*, 108–114. https://doi.org/10.1016/j.conb.2014.07.014

Kirby, S., Tamariz, M., Cornish, H., & Smith, K. (2015). Compression and communication in the cultural evolution of linguistic structure. *Cognition*, *141*, 87–102. https://doi.org/10.1016/j.cognition.2015.03.016

Klimek, P., Kreuzbauer, R., & Thurner, S. (2019). Fashion and art cycles are driven by counter-dominance signals of elite competition: Quantitative evidence from music styles. *Journal of The Royal Society Interface*, *16*(151), 20180731. https://doi.org/10.1098/rsif.2018.0731

Kolodny, O., Creanza, N., & Feldman, M. W. (2015). Evolution in leaps: The punctuated accumulation and loss of cultural innovations. *Proceedings of the National Academy of Sciences*, *112*(49), E6762–E6769. https://doi.org/10.1073/pnas.1520492112

Kotz, S. A., Ravignani, A., & Fitch, W. T. (2018). The Evolution of Rhythm Processing. *Trends in Cognitive Sciences*, *22*(10), 896–910. https://doi.org/10.1016/j.tics.2018.08.002

Laland, K. N., & O'Brien, M. J. (2011). Cultural Niche Construction: An Introduction. *Biological Theory*, *6*(3), 191–202. https://doi.org/10.1007/s13752-012-0026-6

Lala, K., Fedlman, M., & Smee, J. O. (in press). Cultural evolution, gene-culture co-evolution, and cultural niche construction. In *The Oxford Handbook of Cultural Evolution*. Oxford University Press.

Lambert, B., Kontonatsios, G., Mauch, M., Kokkoris, T., Jockers, M., Ananiadou, S., & Leroi, A. M. (2020). The pace of modern culture. *Nature Human Behaviour*, *4*(4), Article 4. https://doi.org/10.1038/s41562-019-0802-4

Leongómez, J. D., Havlíček, J., & Roberts, S. C. (2021). Musicality in human vocal communication: An evolutionary perspective. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *377*(1841), 20200391. https://doi.org/10.1098/rstb.2020.0391

Levinson, S. C., & Gray, R. D. (2012). Tools from evolutionary biology shed new light on the diversification of languages. *Trends in Cognitive Sciences*, *16*(3), 167–173. https://doi.org/10.1016/j.tics.2012.01.007

Little, H., Eryılmaz, K., & de Boer, B. (2017). Signal dimensionality and the emergence of combinatorial structure. *Cognition*, *168*, 1–15. https://doi.org/10.1016/j.cognition.2017.06.011

Livingstone, F. B. (1973). Did the Australopithecines Sing? *Current Anthropology*, *14*(1/2), 25–29.

Lazaridou, A., & Baroni, M. (2020). Emergent multi-agent communication in the deep learning era. *arXiv:2006.02419*. https://doi.org/10.48550/arXiv.2006.02419

Lomax, A. (1968). *Folk song style and culture*. American Assoc. for the Advancement.

Lotem, A., Kolodny, O., & Arbilly, M. (2023). Gene–culture coevolution in the cognitive domain. In J. J. Tehrani, J. Kendal, & R. Kendal (Eds.), *The Oxford Handbook of Cultural Evolution* (p. C66S1-C66N1). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780198869252.013.66

Lumaca, M., & Baggio, G. (2017). Cultural Transmission and Evolution of Melodic Structures in Multi-generational Signaling Games. *Artificial Life*, *23*(3), 406–423. https://doi.org/10.1162/ARTL_a_00238

Lumaca, M., Baggio, G., & Vuust, P. (2021). White matter variability in auditory callosal pathways contributes to variation in the cultural transmission of auditory symbolic systems. *Brain Structure and Function*, *226*(6), 1943–1959. https://doi.org/10.1007/s00429-021-02302-y

Lumaca, M., Bonetti, L., Brattico, E., Baggio, G., Ravignani, A., & Vuust, P. (2023). High-fidelity transmission of auditory symbolic material is associated with reduced right–left neuroanatomical asymmetry between primary auditory regions. *Cerebral Cortex*, bhad009. https://doi.org/10.1093/cercor/bhad009

Lumaca, M., Kleber, B., Brattico, E., Vuust, P., & Baggio, G. (2019). Functional connectivity in human auditory networks and the origins of variation in the transmission of musical systems. *ELife*, *8*, e48710. https://doi.org/10.7554/eLife.48710

Lumaca, M., Ravignani, A., & Baggio, G. (2018). Music Evolution in the Laboratory: Cultural Transmission Meets Neurophysiology. *Frontiers in Neuroscience*, *12*. https://www.frontiersin.org/articles/10.3389/fnins.2018.00246

Lumaca, M., Vuust, P., & Baggio, G. (2022). Network Analysis of Human Brain Connectivity Reveals Neural Fingerprints of a Compositionality Bias in Signaling Systems. *Cerebral Cortex*, *32*(8), 1704–1720. https://doi.org/10.1093/cercor/bhab307

Lupyan, G., & Dale, R. (2010). Language structure is partly determined by social structure. *PloS ONE, 5*(1), e8559. https://doi.org/10.1371/journal.pone.0008559

Ma, W., Fiveash, A., & Thompson, W. F. (2019). Spontaneous emergence of language-like and music-like vocalizations from an artificial protolanguage. *Semiotica*, *2019*(229), 1–23. https://doi.org/10.1515/sem-2018-0139

MacCallum, R. M., Mauch, M., Burt, A., & Leroi, A. M. (2012). Evolution of music by public choice. *Proceedings of the National Academy of Sciences*, *109*(30), 12081–12086. https://doi.org/10.1073/pnas.1203182109

K. Machida, ed. (1944). 日本民謡大観 *[Japanese folk song anthology]* (NHK (Nippon Hōsō Kyōkai)).

Marjieh, R., Harrison, P. M. C., Lee, H., Deligiannaki, F., & Jacoby, N. (2022). *Reshaping musical consonance with timbral manipulations and massive online experiments*. bioRxiv Preprint. https://doi.org/10.1101/2022.06.14.496070

Martins, P. T., & Boeckx, C. (2020). Vocal learning: Beyond the continuum. *PLOS Biology*, *18*(3), e3000672. https://doi.org/10.1371/journal.pbio.3000672

Masataka, N. (2009). The origins of language and the evolution of music: A comparative perspective. *Physics of Life Reviews*, *6*(1), 11–22. https://doi.org/10.1016/j.plrev.2008.08.003

Matsumae, H., Ranacher, P., Savage, P. E., Blasi, D. E., Currie, T. E., Koganebuchi, K., Nishida, N., Sato, T., Tanabe, H., Tajima, A., Brown, S., Stoneking, M., Shimizu, K. K., Oota, H., & Bickel, B. (2021). Exploring correlations in genetic and cultural variation across language families in northeast Asia. *Science Advances*. https://doi.org/10.1126/sciadv.abd9223

Mauch, M., MacCallum, R. M., Levy, M., & Leroi, A. M. (2015). The evolution of popular music: USA 1960–2010. *Royal Society Open Science*, *2*(5), 150081. https://doi.org/10.1098/rsos.150081

McBride, J. M., & Tlusty, T. (2020). *Cross-cultural data shows musical scales evolved to maximise imperfect fifths* (arXiv:1906.06171). arXiv Preprint. https://doi.org/10.48550/arXiv.1906.06171

Mehr, S. A., Krasnow, M. M., Bryant, G. A., & Hagen, E. H. (2021). Origins of music in credible signaling. *Behavioral and Brain Sciences*, *44*. https://doi.org/10.1017/S0140525X20000345

Mehr, S. A., Singh, M., Knox, D., Ketter, D. M., Pickens-Jones, D., Atwood, S., Lucas, C., Jacoby, N., Egner, A. A., Hopkins, E. J., Howard, R. M., Hartshorne, J. K., Jennings, M. V., Simson, J., Bainbridge, C. M., Pinker, S., O'Donnell, T. J., Krasnow, M. M., & Glowacki, L. (2019). Universality and diversity in human song. *Science*, *366*(6468), eaax0868. https://doi.org/10.1126/science.aax0868

Meir, I., Sandler, W., Padden, C., & Aronoff, M. (2010). Emerging sign languages. *Oxford Handbook of Deaf studies, Language, and Education, 2*, 267-280. https://doi.org/10.1093/oxfordhb/9780195390032.013.0018

Mesoudi, A. (2011). *Cultural Evolution: How Darwinian Theory Can Explain Human Culture and Synthesize the Social Sciences*. University of Chicago Press. https://press.uchicago.edu/ucp/books/book/chicago/C/bo8787504.html

Mesoudi, A. (2021). Cultural selection and biased transformation: Two dynamics of cultural evolution. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1828), 20200053. https://doi.org/10.1098/rstb.2020.0053

Mesoudi, A. (in press). Experimental studies of cultural evolution. In *The Oxford Handbook of Cultural Evolution*. Oxford University Press. Preprint: https://doi.org/10.31234/osf.io/qzvxy

Mesoudi, A., & Whiten, A. (2008). The multiple roles of cultural transmission experiments in understanding human cultural evolution. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1509), 3489–3501. https://doi.org/10.1098/rstb.2008.0129

Miller, G. (2000). Evolution of human music through sexual selection. In N. L. Wallin, B. Merker, & S. Brown (Eds.), *The origins of music* (pp. 329–360). The MIT Press.

Miton, H., Wolf, T., Vesper, C., Knoblich, G., & Sperber, D. (2020). Motor constraints influence cultural evolution of rhythm. *Proceedings of the Royal Society B: Biological Sciences*, *287*(1937), 20202001. https://doi.org/10.1098/rspb.2020.2001

Mithen, S. (2007). *The Singing Neanderthals: The Origins of Music, Language, Mind, and Body*. Harvard University Press.

Miyagawa, S., Arévalo, A., & Nóbrega, V. A. (2022). On the representation of hierarchical structure: Revisiting Darwin's musical protolanguage. *Frontiers in Human Neuroscience*, *16*. https://www.frontiersin.org/articles/10.3389/fnhum.2022.1018708

Motamedi, Y., Schouwstra, M., Smith, K., Culbertson, J., & Kirby, S. (2019). Evolving artificial sign languages in the lab: From improvised gesture to systematic sign. *Cognition*, *192*, 103964. https://doi.org/10.1016/j.cognition.2019.05.001

Nakamura, E., & Kaneko, K. (2019). Statistical Evolutionary Laws in Music Styles. *Scientific Reports*, *9*(1), Article 1. https://doi.org/10.1038/s41598-019-52380-6

Nakamura, E. (2021). Conjugate distribution laws in cultural evolution via statistical learning. *Physical Review E*, *104*(3), 034309. https://doi.org/10.1103/PhysRevE.104.034309

Nature Editors. (2022). Nature addresses helicopter research and ethics dumping. Nature, 606, 7. https://doi.org/10.1038/d41586-022-01423-6

Nayak, S., Coleman, P. L., Ladányi, E., Nitin, R., Gustavson, D. E., Fisher, S. E., Magne, C. L., & Gordon, R. L. (2022). The Musical Abilities, Pleiotropy, Language, and Environment (MAPLE) Framework for Understanding Musicality-Language Links Across the Lifespan. *Neurobiology of Language*, 1–50. https://doi.org/10.1162/nol_a_00079

Neureiter, N., Ranacher, P., Efrat-Kowalsky, N., Kaiping, G. A., Weibel, R., Widmer, P., & Bouckaert, R. R. (2022). Detecting contact in language trees: A Bayesian phylogenetic model with horizontal transfer. *Humanities and Social Sciences Communications*, *9*(1), Article 1. https://doi.org/10.1057/s41599-022-01211-7

Niarchou, M., Gustavson, D. E., Sathirapongsasuti, J. F., Anglada-Tort, M., Eising, E., Bell, E., McArthur, E., Straub, P., McAuley, J. D., Capra, J. A., Ullén, F., Creanza, N., Mosing, M. A., Hinds, D. A., Davis, L. K., Jacoby, N., & Gordon, R. L. (2022). Genome-wide association study of musical beat synchronization demonstrates high polygenicity. *Nature Human Behaviour*, *6*(9), Article 9. https://doi.org/10.1038/s41562-022-01359-x

Nishikawa, Y., & Ihara, Y. (2022). Cultural transmission of traditional songs in the Ryukyu Archipelago. *PLOS ONE*, *17*(6), e0270354. https://doi.org/10.1371/journal.pone.0270354

Noble, S. U. (2018). *Algorithms of oppression*. New York University Press.

Nolan, F., & Jeon, H.-S. (2014). Speech rhythm: A metaphor? *Philosophical Transactions of the Royal Society B: Biological Sciences*, *369*(1658), 20130396. https://doi.org/10.1098/rstb.2013.0396

Nölle, J. (2021). *How language adapts to the environment: An evolutionary, experimental approach*. PhD thesis, University of Edinburgh. https://doi.org/10.7488/era/2144

Oord, A. van den, Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., Kalchbrenner, N., Senior, A., & Kavukcuoglu, K. (2016). *WaveNet: A Generative Model for Raw Audio* (arXiv:1609.03499). arXiv. https://doi.org/10.48550/arXiv.1609.03499

Ozaki, Y., Tierney, A., Pfordresher, P., Mcbride, J., Benetos, E., Proutskova, P., Chiba, G., Liu, F., Jacoby, N., Purdy, S., Opondo, P., Fitch, T., Hegde, S., Rocamora, M., Thorne, R., Nweke, F. E., Sadaphal, D., Sadaphal, P., Hadavi, S., … Savage, P. E. (2023, 採録許可). Globally, songs and instrumental melodies are slower, higher, and use more stable pitches than speech [Stage 2 Registered Report]. *Peer Community In Registered Reports*. Preprint: https://doi.org/10.31234/osf.io/jr9x7

Pamjav, H., Juhász, Z., Zalán, A., Németh, E., & Damdin, B. (2012). A comparative phylogenetic study of genetics and folk music. *Molecular Genetics and Genomics*, *287*(4), 337–349. https://doi.org/10.1007/s00438-012-0683-y

Passmore, S., & Jordan, F. M. (2020). No universals in the cultural evolution of kinship terminology. *Evolutionary Human Sciences*, *2*, e42. https://doi.org/10.1017/ehs.2020.41

Passmore, S., Wood, A. L. C., Barbieri, C., Shilton, D., Daikoku, H., Atkinson, Q. D., and Savage, P. E. (2023). Independent histories underlie global musical, linguistic, and genetic diversity. *PsyArXiv* preprint: https://doi.org/10.31234/osf.io/pty34

Patel, A. D. (2008). *Music, Language, and the Brain*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195123753.001.0001

Patel, A. D. (2018). Music as a Transformative Technology of the Mind: An Update. In H. Honing (Ed.), *The Origins of Musicality*. MIT Press. https://direct.mit.edu/books/book/4115/chapter/170183/Music-as-a-Transformative-Technology-of-the-Mind

Patel, A. D. (2021). Vocal learning as a preadaptation for the evolution of human beat perception and synchronization. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1835), 20200326. https://doi.org/10.1098/rstb.2020.0326

Patel, A. D., Iversen, J. R., Bregman, M. R., & Schulz, I. (2009). Studying Synchronization to a Musical Beat in Nonhuman Animals. *Annals of the New York Academy of Sciences*, *1169*(1), 459–469. https://doi.org/10.1111/j.1749-6632.2009.04581.x

Pereltsvaig, A., & Lewis, M. W. (2015). *The Indo-European Controversy: Facts and Fallacies in Historical Linguistics*. Cambridge University Press.

Phillips, E., & Brown, S. (2022). Vocal imprecision as a universal constraint on the structure of musical scales. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-24035-6

Podlipniak, P. (2022). Pitch syntax as part of an ancient protolanguage. *Lingua*, *271*, 103238. https://doi.org/10.1016/j.lingua.2021.103238

Poeppel, D., & Assaneo, M. F. (2020). Speech rhythms and their neural foundations. *Nature Reviews Neuroscience*, *21*(6), 322–334. https://doi.org/10.1038/s41583-020-0304-4

Popescu, T., Walther, J., & Rohrmeier, M. (2022). *Core principles of melodic organisation emerge from transmission chains with random melodies*. PsyArXiv preprint. https://doi.org/10.31234/osf.io/vg9fz

Pouw, W., Proksch, S., Drijvers, L., Gamba, M., Holler, J., Kello, C., Schaefer, R. S., & Wiggins, G. A. (2021). Multilevel rhythms in multimodal communication. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1835), 20200334. https://doi.org/10.1098/rstb.2020.0334

Ravignani, A., Delgado, T., & Kirby, S. (2016). Musical evolution in the lab exhibits rhythmic universals. *Nature Human Behaviour*, *1*(1), Article 1. https://doi.org/10.1038/s41562-016-0007

Ravignani, A., Thompson, B., Grossi, T., Delgado, T., & Kirby, S. (2018). Evolving building blocks of rhythm: How human cognition creates music via cultural transmission. *Annals of the New York Academy of Sciences*, *1423*(1), 176–187. https://doi.org/10.1111/nyas.13610

Ravignani, A., & Boer, B. de. (2021). Joint origins of speech and music: Testing evolutionary hypotheses on modern humans. *Semiotica*, *2021*(239), 169–176. https://doi.org/10.1515/sem-2019-0048

Raviv, L., Meyer, A., & Lev-Ari, S. (2019). Compositional structure can emerge without generational transmission. *Cognition*, *182*, 151–164. https://doi.org/10.1016/j.cognition.2018.09.010

Raviv, L., Meyer Antje, & Lev-Ari Shiri. (2019). Larger communities create more systematic languages. *Proceedings of the Royal Society B: Biological Sciences*, *286*(1907), 20191262. https://doi.org/10.1098/rspb.2019.1262

Raviv, L., Meyer, A., & Lev-Ari, S. (2020). The Role of Social Network Structure in the Emergence of Linguistic Structure. *Cognitive Science*, *44*(8), e12876. https://doi.org/10.1111/cogs.12876

Raviv, L., de Heer Kloots, M., & Meyer, A. (2021). What makes a language easy to learn? A preregistered study on how systematic structure and community size affect language learnability. *Cognition*, *210*, 104620. https://doi.org/10.1016/j.cognition.2021.104620

Raviv, L., & Kirby, S. (2023). Self domestication and the cultural evolution of language. In *The Oxford Handbook of Cultural Evolution*. Oxford University Press.

Reybrouck, M., & Podlipniak, P. (2019). Preconceptual Spectral and Temporal Cues as a Source of Meaning in Speech and Music. *Brain Sciences*, *9*(3), Article 3. https://doi.org/10.3390/brainsci9030053

Richerson, P. J., & Boyd, R. (1978). A dual inheritance model of the human evolutionary process I: Basic postulates and a simple model. *Journal of Social and Biological Structures*, *1*(2), 127–154. https://doi.org/10.1016/S0140-1750(78)80002-5

Richman, B. (1987). Rhythm and melody in gelada vocal exchanges. *Primates*, *28*(2), 199–223. https://doi.org/10.1007/BF02382570

Rouse, A. A., Patel, A. D., & Kao, M. H. (2021). Vocal learning and flexible rhythm pattern perception are linked: Evidence from songbirds. *Proceedings of the National Academy of Sciences*, *118*(29), e2026130118. https://doi.org/10.1073/pnas.2026130118

Rzeszutek, T., Savage, P. E., & Brown, S. (2012). The structure of cross-cultural musical diversity. *Proceedings of the Royal Society B: Biological Sciences*. https://doi.org/10.1098/rspb.2011.1750

Sachs, C. (1940). *The History of Musical Instruments*. W.W.Norton & Company Inc.

Sadakata, M., Desain, P., & Honing, H. (2006). The Bayesian Way to Relate Rhythm Perception and Production. *Music Perception: An Interdisciplinary Journal*, *23*(3), 269–288. https://doi.org/10.1525/mp.2006.23.3.269

Salganik, M. J., Dodds, P. S., & Watts, D. J. (2006). Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market. *Science*, *311*(5762), 854–856. https://doi.org/10.1126/science.1121066

Salganik, M. J., & Watts, D. J. (2008). Leading the Herd Astray: An Experimental Study of Self-fulfilling Prophecies in an Artificial Cultural Market. *Social Psychology Quarterly*, *71*(4), 338–355. https://doi.org/10.1177/019027250807100404

Sandler, W., Meir, I., Padden, C., & Aronoff, M. (2005). The emergence of grammar: Systematic structure in a new language. *Proceedings of the National Academy of Sciences, 102*(7), 2661-2665. https://doi.org/10.1073/pnas.0405448102

Sandler, W., Aronoff, M., Meir, I., & Padden, C. (2011). The gradual emergence of phonological form in a new language. *Natural Language & Linguistic Theory*, *29*(2), 503–543. https://doi.org/10.1007/s11049-011-9128-2

Savage, P. E. (2018). Alan Lomax's Cantometrics Project: A comprehensive review. *Music & Science*, 1, 1–19. https://doi.org/10.1177/2059204318786084

Savage, P. E. (2019). Universals. In J. L. Sturman (Ed.), *SAGE International Encyclopedia of Music and Culture* (pp. 2282–2285). SAGE Publications. https://doi.org/10.4135/9781483317731.n759

Savage, P. E., Brown, S., Sakai, E., & Currie, T. E. (2015). Statistical universals reveal the structures and functions of human music. *Proceedings of the National Academy of Sciences*, *112*(29), 8987–8992. https://doi.org/10.1073/pnas.1414495112

Savage, P. E., Loui, P., Tarr, B., Schachner, A., Glowacki, L., Mithen, S., & Fitch, W. T. (2021). Music as a coevolved system for social bonding. *Behavioral and Brain Sciences*, *44*. https://doi.org/10.1017/S0140525X20000333

Savage, P. E., Passmore, S., Chiba, G., Currie, T. E., Suzuki, H., & Atkinson, Q. D. (2022). Sequence alignment of folk song melodies reveals cross-cultural regularities of musical evolution. *Current Biology*, *32*(6), 1395-1402.e8. https://doi.org/10.1016/j.cub.2022.01.039

Schouwstra, M., Smith, K., & Kirby, S. (2020). *The emergence of word order conventions: Improvisation, interaction and transmission*. PsyArXiv. https://doi.org/10.31234/osf.io/wdfu2

Ségurel, L., & Bon, C. (2017). On the evolution of lactase persistence in humans. *Annual Review of Genomics and Human Genetics*, 18(1), 297–319. https://doi.org/10.1146/annurev-genom-091416-035340

Selten, R., & Warglien, M. (2007). The emergence of simple languages in an experimental coordination game. *Proceedings of the National Academy of Sciences, 104*(18), 7361–7366. https://doi.org/10.1073/pnas.0702077104

Senghas, A., Kita, S., & Ozyurek, A. (2004). Children creating core properties of language: Evidence from an emerging sign language in Nicaragua. *Science, 305*(5691), 1779-1782. https://doi.org/10.1126/science.1100199

Serrà, J., Corral, Á., Boguñá, M., Haro, M., & Arcos, J. L. (2012). Measuring the Evolution of Contemporary Western Popular Music. *Scientific Reports*, *2*(1), Article 1. https://doi.org/10.1038/srep00521

Shanahan, D., & Albrecht, J. (2019). Examining the Effect of Oral Transmission on Folksongs. *Music Perception*, *36*(3), 273–288. https://doi.org/10.1525/mp.2019.36.3.273

Singh, M., & Mehr, S. A. (2023). Universality, domain-specificity, and development of psychological responses to music. *Nature Reviews Psychology*. 1-14. https://doi.org/10.1038/s44159-023-00182-z

Smith, K., Perfors, A., Fehér, O., Samara, A., Swoboda, K., & Wonnacott, E. (2017). Language learning, language use and the evolution of linguistic variation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *372*(1711), 20160051. https://doi.org/10.1098/rstb.2016.0051

Street, S. E., Eerola, T., & Kendal, J. R. (2022). The role of population size in folk tune complexity. *Humanities and Social Sciences Communications*, *9*(1), Article 1. https://doi.org/10.1057/s41599-022-01139-y

Tan, Y. T., McPherson, G. E., Peretz, I., Berkovic, S. F., & Wilson, S. J. (2014). The genetic basis of music ability. *Frontiers in Psychology*, *5*. https://www.frontiersin.org/articles/10.3389/fpsyg.2014.00658

ten Cate, C., & Honing, H. (in press). *Precursors of Music and Language in Animals*. In *The Oxford Handbook of Language and Music*. Oxford University Press. https://doi.org/10.31234/osf.io/4zxtr

Theisen-White, C., Kirby, S., & Oberlander, J. (2011). Integrating the Horizontal and Vertical Cultural Transmission of Novel Communication Systems. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *33*(33). https://escholarship.org/uc/item/40t7578c

Thompson, W. F., Marin, M. M., & Stewart, L. (2012). Reduced sensitivity to emotional prosody in congenital amusia rekindles the musical protolanguage hypothesis. *Proceedings of the National Academy of Sciences*, *109*(46), 19027–19032. https://doi.org/10.1073/pnas.1210344109

Thompson, B., Kirby, S., & Smith, K. (2016). Culture shapes the evolution of cognition. *Proceedings of the National Academy of Sciences, 113*(16), 4530-4535. https://doi.org/10.1073/pnas.1523631113

Tierney, A. T., Russo, F. A., & Patel, A. D. (2011). The motor origins of human and avian song structure. *Proceedings of the National Academy of Sciences*, *108*(37), 15510–15515. https://doi.org/10.1073/pnas.1103882108

Toussaint, G. (2013). *The Geometry of Musical Rhythm: What Makes a "Good" Rhythm Good?* Chapman & Hall/CRC.

van der Weij, B., Pearce, M. T., & Honing, H. (2017). A Probabilistic Model of Meter Perception: Simulating Enculturation. *Frontiers in Psychology*, *8*. https://www.frontiersin.org/articles/10.3389/fpsyg.2017.00824

Vanden Bosch der Nederlanden, C.M., Qi, X., Sequeira, S., Seth, P., Grahn, J.A., Joanisse, M.F., and Hannon, E.E. (2022). Developmental changes in the categorization of speech and song. *Developmental Science*, e13346. https://doi.org/10.1111/desc.13346

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is All you Need. *Advances in Neural Information Processing Systems*, *30*. https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html

Verhoef, T., Kirby, S., & de Boer, B. (2016). Iconicity and the Emergence of Combinatorial Structure in Language. *Cognitive Science*, *40*(8), 1969–1994. https://doi.org/10.1111/cogs.12326

Verhoef, T., & Ravignani, A. (2021). Melodic Universals Emerge or Are Sustained Through Cultural Evolution. *Frontiers in Psychology*, *12*. https://www.frontiersin.org/articles/10.3389/fpsyg.2021.668300

Wallin, N. L., Merker, B., & Brown, S. (Eds.). (2000). *The origins of music*. The MIT Press.

Wesseldijk, L. W., Gordon, R. L., Mosing, M. A., & Ullén, F. (2021). Music and verbal ability—A twin study of genetic and environmental associations. *Psychology of Aesthetics, Creativity, and the Arts*. https://doi.org/10.1037/aca0000401

Woensdregt, M., Cummins, C., & Smith, K. (2021). A computational model of the cultural co-evolution of language and mindreading. *Synthese*, *199*(1), 1347–1385. https://doi.org/10.1007/s11229-020-02798-7

Youngblood, M. (2019). Cultural transmission modes of music sampling traditions remain stable despite delocalization in the digital age. *PLOS ONE*, *14*(2), e0211860. https://doi.org/10.1371/journal.pone.0211860

Youngblood, M., Ozaki, Y., & Savage, P. E. (2023). Cultural evolution and music. In J. J. Tehrani, J. R. Kendal, & R. L. Kendal (Eds.), *The Oxford Handbook of Cultural Evolution* (p. C42S1-C42N14). Oxford University Press. https://doi.org/10.31234/osf.io/xsb7v

Yuan, Y., Cronin, C., Müllensiefen, D., Fujii, S., & Savage, P. E. (In Press). Perceptual and automated estimates of infringement in 40 music copyright cases. *Transactions* *of the International Society for Music Information Retrieval*: https://doi.org/10.31234/osf.io/dzypn

3. Globally, songs and instrumental melodies are slower, higher, and use more stable pitches than speech [Stage 2 Registered Report][2]

[2] Ozaki, Tierney, Pfordresher, Mcbride, Benetos, Proutskova, Chiba, Liu, Jacoby, Purdy, Opondo, Fitch, Hegde, Rocamora, Thorne, Nweke, Sadaphal, Sadaphal, Hadavi, … Savage. *PsyArxiv Preprint* (2022).

Authors: Yuto Ozaki[@1], Adam Tierney[2], Peter Q. Pfordresher[3], John McBride[4], Emmanouil Benetos[5], Polina Proutskova[5], Gakuto Chiba[6], Fang Liu[7], Nori Jacoby[8], Suzanne C. Purdy[9], Patricia Opondo[10], W. Tecumseh Fitch[11], Shantala Hegde[12], Martín Rocamora[13], Rob Thorne[14], Florence Nweke[15], Dhwani P. Sadaphal[11], Parimal M. Sadaphal[16], Shafagh Hadavi[1], Shinya Fujii[6], Sangbuem Choo[1], Marin Naruse[6], Utae Ehara[18], Latyr Sy[19], Mark Lenini Parselelo[20,21], Manuel Anglada-Tort[22], Niels Chr. Hansen[23], Felix Haiduk[11], Ulvhild Færøvik[24], Violeta Magalhães[25], Wojciech Krzyżanowski[26], Olena Shcherbakova[27], Diana Hereld[28], Brenda Suyanne Barbosa[11], Marco Antonio Correa Varella[29], Mark van Tongeren[30], Polina Dessiatnitchenko[31], Su Zar Zar[32], Iyadh El Kahla[33], Olcay Muslu[34], Jakelin Troy[35], Teona Lomsadze[36], Dilyana Kurdova[37], Cristiano Tsope[38], Daniel Fredriksson[39], Aleksandar Arabadjiev[40], Jehoshaphat Philip Sarbah[41], Adwoa Arhine[42], Tadhg Ó Meachair[43], Javier Silva-Zurita[44,45], Ignacio Soto-Silva[44,45], Neddiel Elcie Muñoz Millalonco[46], Rytis Ambrazevičius[47], Psyche Loui[48], Andrea Ravignani[17], Yannick Jadoul[53], Pauline Larrouy-Maestri[8,49], Camila Bruder[8], Tutushamum Puri Teyxokawa[50], Urise Kuikuro[51], Rogerdison Natsitsabui[51], Nerea Bello Sagarzazu[52], Limor Raviv[52,53], Minyu Zeng[54], Shahaboddin Dabaghi Varnosfaderani[55], Juan Sebastián Gómez-Cañón[56], Kayla Kolff[57], Christina Vanden Bosch der Nederlanden[58], Meyha Chhatwal[58], Ryan Mark David[58], I Putu Gede Setiawan[59], Great Lekakul[60], Vanessa Nina Borsan[1,61], Nozuko Nguqu[10], Patrick E. Savage[@6,9]

[@]Correspondence: yozaki@sfc.keio.ac.jp and psavage@sfc.keio.ac.jp

NB: Order of authors other than first and last authors is based on the order in which they joined the project. See Author Contributions statement for detailed information.

[1]Graduate School of Media and Governance, Keio University, Japan
[2]Department of Psychological Sciences, Birkbeck, University of London, UK
[3]Department of Psychology, University at Buffalo, State University of New York, USA
[4]Institute for Basic Science, South Korea
[5]School of Electronic Engineering and Computer Science, Queen Mary University of London, UK
[6]Faculty of Environment and Information Studies, Keio University, Japan
[7]School of Psychology & Clinical Language Sciences, University of Reading, UK
[8]Max-Planck Institute for Empirical Aesthetics, Germany
[9]School of Psychology, University of Auckland, New Zealand; Eisdell Moore Centre for Hearing and Balance Research
[10]School of Arts, University of KwaZulu-Natal, South Africa
[11]Department of Behavioral and Cognitive Biology / Department of Musicology, University of Vienna, Austria
[12]Music Cognition Lab, Department of Clinical Psychology, National Institute of Mental Health and Neuro Sciences, India
[13]Universidad de la República, Uruguay
[14]School of Music, Victoria University of Wellington, New Zealand
[15]Department of Creative Arts, University of Lagos, Nigeria
[16]Independent researcher, India
[17]Department of Human Neurosciences, Sapienza University of Rome, Italy
[18]Haponetay, Shimizu-cho, Hokkaido, Japan
[19]Independent researcher, Japan/Senegal
[20]Memorial University of Newfoundland, Canada
[21]Department of Music and Dance, Kenyatta University, Kenya
[22]Faculty of Music, University of Oxford, UK
[23]Aarhus Institute of Advanced Studies, Aarhus University, Denmark
[24]Institute of Biological and Medical Psychology, Department of Psychology, University of Bergen, Norway
[25]Centro de Linguística da Universidade do Porto, University of Porto, Portugal
[26]Adam Mickiewicz University, Poland
[27]Max-Planck Institute for the Science of Human History, Germany
[28]Clinical Psychology, Pepperdine University, USA
[29]Department of Experimental Psychology, Institute of Psychology, University of São Paulo, Brazil
[30]Independent researcher, Taiwan
[31]School of International Liberal Studies, Waseda University, Japan
[32]Headmistress, The Royal Music Academy, Yangon, Myanmar
[33]Department of Cultural Policy, University of Hildesheim, Germany
[34]Independent researcher, Turkey
[35]Sydney Environment Institute, University of Sydney, Australia
[36]International Research Center for Traditional Polyphony of the Tbilisi State Conservatoire, Georgia
[37]South-West University ""Neofit Rilski", Bulgaria
[38]Universidade de Aveiro, Portugal
[39]Dalarna University, Sweden
[40]Independent researcher, Austria
[41]Department of Music and Dance, University of Cape Coast, Ghana
[42]Department of Music, University of Ghana, Ghana
[43]Department of Ethnomusicology and Folklore, Indiana University, USA
[44]Department of Humanities and Arts, University of Los Lagos, Chile
[45]Millennium Nucleus on Musical and Sound Cultures (CMUS), Chile
[46]Traditional performer and culture bearer, Chile
[47]Kaunas University of Technology and Lithuanian Academy of Music and Theatre, Lithuania

Abstract

What, if any, similarities and differences between music and speech are consistent across cultures? Both music and language are found in all known human societies and are argued to share evolutionary roots and cognitive resources, yet no studies have compared similarities and differences between song, speech, and instrumental music across languages on a global scale. In this Registered Report, we analyze a novel dataset of 300 high-quality annotated audio recordings representing matched sets of singing, recitation, conversational speech, and instrumental music from our 75[1] coauthors whose 55 1st/heritage languages span 21 language families to find strong evidence for cross-culturally consistent differences and similarities between music and language. Of our six pre-registered predictions, five were strongly supported: relative to speech, songs use 1) higher pitch, 2) slower temporal rate, and 3) more stable pitches, while both songs and speech used similar 4) pitch interval size, and 5) timbral brightness. Our 6th prediction that song and speech would show similar pitch declination was inconclusive, with exploratory analysis suggesting that songs tend to follow an arched contour while speech contours tend to decline overall but end with a slight rise. Because our non-representative language sample and unusual design involving coauthors as participants could affect our results, we also performed robustness analyses - including a parallel reanalysis of a previously published dataset of 418 song/speech recordings from 209 individuals whose 16 languages span 11 language families (Hilton & Moser et al., 2022, *Nature Human Behaviour*) - which confirmed that our conclusions are robust to these potential biases. Exploratory analyses identified additional features such as phrase length, intensity, and rhythmic/melodic regularity that also consistently distinguish song from speech, and suggest that such features also vary along a “musi-linguistic” continuum in a cross-culturally consistent manner when including instrumental melodies and recited lyrics. Further exploratory analysis suggests that pitch height is the only consistently sexually dimorphic feature (female singing/speaking is almost one octave higher than male on average), and that other factors such as musical training and recording context may also interact to influence the magnitude of song-speech differences. Our study provides strong empirical evidence for the existence of cross-cultural regularities in music and speech.

3.1. Introduction

Language and music are both found universally across cultures, yet in highly diverse forms (Evans & Levinson, 2009; Jacoby et al., 2020; Mehr et al., 2019; Savage 2019), leading many to speculate on their evolutionary functions and possible coevolution (e.g., Darwin, 1871; Haiduk & Fitch, 2022; Mehr et al., 2021; Patel, 2008; Savage et al., 2021; Valentova et al., 2019). Yet such speculation still lacks empirical data to answer the question: what similarities and differences between music and language are shared cross-culturally?

[48] Music, Imaging and Neural Dynamics Lab, Northeastern University, USA
[49] Max Planck-NYU Center for Language, Music, and Emotion (CLaME), USA & Germany
[50] Txemim Puri Project - Puri Language Research, Vitalization and Teaching/ Recording and Preservation of Puri History and Culture, Brasil
[51] Independent researcher, Brazil
[52] University of Glasgow, UK
[53] Max Planck Institute for Psycholinguistics, Netherlands
[54] Rhode Island School of Design, USA
[55] Institute for English & American Studies (IEAS), Goethe University of Frankfurt am Main, Germany
[56] Music Technology Group, Universitat Pompeu Fabra, Spain
[57] Institute of Cognitive Science, University of Osnabrück, Germany
[58] Department of Psychology, University of Toronto Mississsauga, Canada
[59] Independent researcher, Tokyo, Japan
[60] Faculty of Fine Arts, Chiang Mai University, Thailand
[61] University of Lille, France

Although comparative research has revealed distinct and shared *neural* mechanisms for music and language (Albouy et al., 2020; Doelling et al., 2019; Morrill et al., 2015; Patel, 2008, 2011; Peretz, 2009; Rogalsky et al., 2011), there has been relatively less comparative analysis of *acoustic* attributes of music and language (e.g., Ding et al., 2017; Patel et al., 2006), and even fewer that directly compare the two most widespread forms of music and language that use the same production mechanism: vocal music (song) and spoken language (speech).

Cross-cultural analyses have identified "statistical universals" shared by most of the world's musics and/or languages (Bickel, 2011; Brown, 1991; Brown and Jordiana, 2013; Savage et al., 2015). In music, these include regular rhythms, discrete pitches, small melodic intervals, and a predominance of songs with words (rather than instrumental music or wordless songs) (Mehr et al., 2019; Savage et al., 2015). However, non-signed languages also use the voice to produce words, and other proposed musical universals may also be shared with language (e.g., discrete pitch in tone languages; regular rhythms in "syllable-timed" / "stress-timed" languages; use of higher pitch when vocalizing to infants) (Haiduk & Fitch, 2022; Hilton et al., 2022; Ozaki et al., 2022; Patel, 2008; Tierney et al., 2011). Moreover, vocal parameters of speech and singing, such as fundamental frequency and vocal tract length as estimated from formant frequencies, are strongly intercorrelated in both men and women (Valentova et al., 2019).

Many hypotheses make predictions about cross-cultural similarities and differences between song and speech. For example, the social bonding hypothesis (Savage et al., 2021) predicts that song is more predictably regular than speech to facilitate synchronization and social bonding. In contrast, Tierney et al.'s (2011) motor constraint hypothesis predicts similarities in pitch interval size and melodic contour due to shared constraints on sung and spoken vocalization. Similarly, the sexual selection hypothesis (Valentova et al., 2019) predicts similarities between singing and speaking due to their redundant functions as 'backup signals' indicating similar underlying mate qualities (e.g., body size). Finally, culturally relativistic hypotheses instead predict neither regular cross-cultural similarities nor differences between song and speech, but rather predict that relationships between song and speech are strongly culturally dependent without any universal regularities (List, 1971).

Culturally relativistic hypotheses appear to be dominant among ethnomusicologists. For example, in a Jan 13, 2022 email to the International Council for Traditional Music (ICTM) email list entitled "What is song?", ICTM Vice-President Don Niles requested definitions for "song" that might distinguish it from "speech" cross-culturally. Much debate ensued, but the closest to such a definition that appeared to emerge was the following conclusion published by Savage et al. (2015) based on a comparative analysis of 304 audio recordings of music from around the world:

> *"Although we found many statistical universals, absolute musical universals did not exist among the candidates we were able to test. The closest thing to an absolute universal was Lomax and Grauer's [1968] definition of a song as a* ***vocalization using "discrete pitches or regular rhythmic patterns or both,"*** *which applied to almost the entire sample, including instrumental music. However, three musical examples from Papua New Guinea containing combinations of friction blocks, swung slats, ribbon reeds, and moaning voices contained neither discrete pitches nor an isochronous beat. It should be noted that the editors of the Encyclopedia did not*

> *adopt a formal definition of music in choosing their selections. We thus assume that they followed the common practice in ethnomusicology of defining music as "humanly organized sound" [Blacking, 1973] other than speech, with the distinction between speech and music being left to each culture's emic (insider, subjective) conceptions, rather than being defined objectively by outsiders. Thus, our analyses suggest that there is* ***no absolutely universal and objective definition of music, but that Lomax and Grauer's definition may offer a useful working definition to distinguish music from speech."*** (emphasis added)

Importantly, however, Savage et al.'s conclusion was based only on an analysis of music, thus the contrast with speech is speculative and not based on comparative data.

Some studies have identified differences between speech and song in specific languages, such as song being slower and higher-pitched (Hansen et al., 2020; Merrill & Larrouy-Maestri, 2017; Sharma et al., 2021; Vanden Bosch der Nederlanden et al., 2022). However, a lack of annotated cross-cultural recordings of matched speaking and singing has hampered attempts to establish cross-cultural relationships between speech and song (cf. Blasi et al., 2022). The available dataset closest to our study is Hilton, Moser, et al.'s (2022) recordings sampled from 21 societies. Their dataset covers 11 language families and each participant produced a set of adult-directed and infant-directed song and speech. However, their dataset was designed to independently compare adult-directed vs. infant-directed versions of song and of speech, and they did not directly compare singing vs. speaking. We performed exploratory analyses of their dataset (Ozaki et al., 2022), but found that since their dataset does not include manual annotations for acoustic units (e.g. note, syllable, sentence, phrase, etc.), it is challenging to analyze and compare key structural aspects such as pitch intervals, pitch contour shape, or note/syllable duration. While automatic segmentation can be effective for segmenting some musical instruments and animal songs (e.g., percussion instruments [Durojaye et al., 2021]; bird song notes separated by micro-breaths [Roeske et al. 2020]), we found they did not provide satisfactory segmentation results compared to human manual annotation for the required task of segmenting continuous song/speech into discrete acoustic units such as notes or syllables (cf. Fig. S6). For example, Mertens' (2022) automated segmentation algorithm used by Hilton et al. (2022) mis-segmented two out of the first three words "by a lonely" from the English song used in our pilot analyses ("The Fields of Athenry"), over-segmenting "by" into "b-y", and under-segmenting "lonely" by failing to divide it into "lone-ly" (cf. Fig. S6 for systematic comparison of annotation by automated methods and by humans speaking five different languages from our pilot data).

Our study overcomes these issues by creating a unique dataset of matched singing and speaking of diverse languages, with each recording manually segmented into acoustic units (e.g., syllables, notes, phrases) by the coauthor who recorded it in their own 1st/heritage language. Furthermore, because singing and speaking exist on a broader "musi-linguistic" spectrum including forms such as instrumental music and poetry recitation (Brown, 2000; Leongómez et al., 2022; Tsur and Gafni, 2022), we collected four types of recordings to capture variation across this spectrum: **1) singing**, **2) recitation** of the sung lyrics, **3) spoken description** of the song, and **4) instrumental** version of the sung melody (Fig. 3.1). The spoken description represents a sample of naturalistic speech. In contrast, the lyrics recitation allows us to control for potential differences between the words and rhythmic structures used in song vs. natural speech by comparing the exact same lyrics when sung vs. spoken, but as a result may be more analogous to poetry than to natural speech. The instrumental recording is included to capture the full musi-linguistic spectrum from instrumental music to spoken language, allowing us to determine how similar/different music and speech are when using the same effector system (speech vs. song) versus a different system (speech vs. instrument).

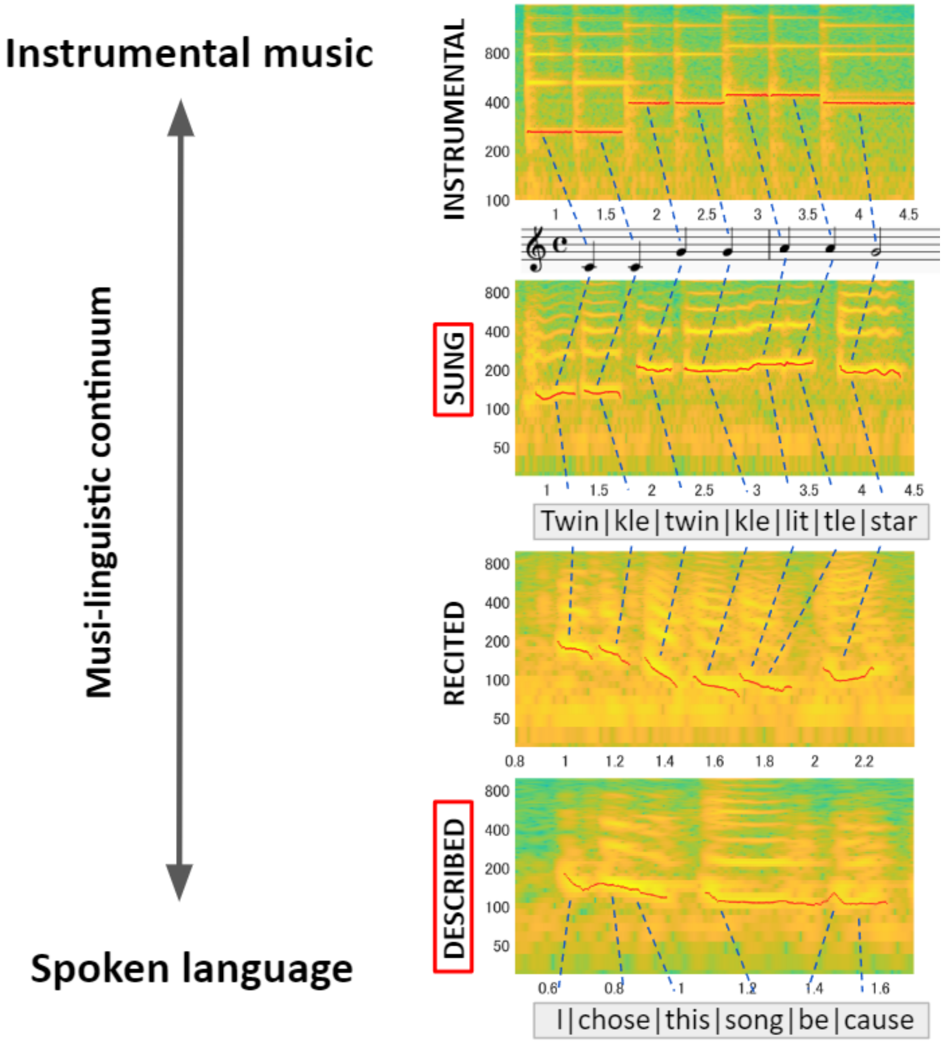


Figure 3.1. **Example excerpts of the four recording types collected in this study, arranged in a "musi-linguistic continuum" from instrumental music to spoken language.** Spectrograms (x-axis: time [seconds], y-axis: frequency [Hz]) of the four types of recordings are displayed on the right-hand side (excerpts of author Savage performing/describing "Twinkle Twinkle", using a piano for the instrumental version). Blue dashed lines show the schematic illustration of the mapping between the audio signal and acoustic units (here syllables/notes). For this Registered Report, we focus our confirmatory hypothesis only on comparisons between singing and spoken description (red rectangles), with recited and instrumental versions saved for post-hoc exploratory analysis.

3.1.1 Study aims and hypotheses

Our study aims to determine cross-cultural similarities and differences between speech and song. Many evolutionary hypotheses result in similar predicted similarities/differences between speech and song: for example, song may use more stable pitches than speech in order to signal desirability as a mate and/or to facilitate harmonized singing, and by association bond groups together or signal their bonds to outside groups (Savage et al., 2021b). Such similarities and differences between song and speech could arise through a combination of purely cultural evolution, purely biological evolution, or some combination of gene-culture coevolution (Patel, 2018; Savage et al., 2021; Hoeschele & Fitch, 2022). Rather than try to disambiguate such ultimate theories, we focus on testing more proximate predictions about similarities and differences in the acoustic features of song and speech, which can then be used to develop more cross-culturally general ultimate theories in future research. Through literature review and pilot analysis (see Section S1.4), we settled on six features we believe we can reliably test for predicted similarities/differences: **1) pitch height, 2) temporal rate, 3) pitch stability, 4) timbral brightness, 5) pitch interval size**, and **6) pitch declination** (cf. Table 1). Detailed speculation on the possible mechanisms underlying potential similarities and differences are described in the Supplementary Discussion section (S2).

Table 3.1. Registered Report Design Planner. Includes six hypotheses (H1-H6).

Question	Hypothesis	Sampling plan	Analysis plan	Rationale for deciding the test sensitivity	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes	Actual outcome
Are any acoustic features reliably **different** between song and speech across cultures?	1) Song uses **higher pitch** than speech	**n=81 pairs of audio recordings** of song/speech, with each pair sung/spoken by the same person **(Fig. 3.3)**. Recruitment was opportunistic based on collaborator networks aiming to maximize global diversity and achieve greater than 95% a priori power even if some data has to be excluded (see **Sec. 2.2** for inclusion/ exclusion criteria).	Meta-analysis framework **(Fig. 3.2)** calculates a paired effect size for **pitch height (*f_0*)** for each song/ speech pair and tests whether the population effect size (relative effect p_{re}) is significantly larger than 0.5.	Power analysis estimate of **minimum n=60 pairs** was based on converting Brysbaert's (2019) suggested Smallest Effect Size Of Interest (SESOI) of Cohen's d=0.4 to the corresponding p_{re} = 0.61. We control for multiple comparisons using false discovery rate (Benjamini-Hochberg step-up method; family-wise α = .05; β = .95).	The null hypothesis of no difference in ***f_0*** between sung and spoken pitch height is rejected if the population effect size is **significantly larger than p_{re} = 0.5**. Otherwise, we neither reject nor accept the hypothesis.	Our design cannot falsify specific ultimate theories (e.g., social bonding hypothesis, motor constraint hypothesis), but can falsify cultural relativistic **theories that argue against general cross-cultural regularities** in song-speech relationships.	All three hypothesized differences between song and speech (pitch height, temporal rate, and pitch stability) were confirmed
	2) Song is **slower** than speech	Same as H1, but for **temporal rate (*inter-onset interval (IOI) rate*)** instead of **pitch height (f_0)**					
	3) Song uses **more stable pitches** than speech	Same as H1, but for **pitch stability** (-|**Δ*f_0***|) instead of **pitch height**					
Are any acoustic features reliably **shared** between song and speech across cultures?	4) Song and speech use **similar timbral brightness**	Same as H1.	Same as H1, except test whether the effect size for timbral brightness is significantly **smaller** than the SESOI.	Same as H1.	The null hypothesis of ***spectral centroid*** of singing being meaningfully lower or higher than speech is rejected if the population effect size is **significantly within the SESOI** (0.39<p_{re} <0.61, corresponding to ±0.4 of Cohen's d. Otherwise, we neither reject nor accept the hypothesis.	Same as H1.	The hypothesized similarities in timbral brightness and pitch interval size were confirmed
	5) Song and speech use **similar sized pitch intervals**	Same as H4, but for **pitch interval size (*f_0* *ratio*)** instead of **timbral brightness.**					
	6) Song and speech use **similar pitch contours**	Same as H4, but for **pitch declination (*sign* of *f_0* *slope*)** instead of **timbral brightness.**					The hypothesized similarity in pitch contour was neither rejected nor confirmed.

3.1.2 Analysis plan

We test two types of hypotheses, corresponding to the hypothesis of difference and the hypothesis of similarity, respectively. Formally, one type of null hypothesis is whether the effect size of the difference between song and speech for a given feature is null. This hypothesis will be applied to the prediction of the statistical difference. Another type of null hypothesis is whether the effect size of the feature exceeds the smallest effect size of interest (SESOI) (Lakens, 2017). This hypothesis will be applied to the prediction of statistical similarity. In this study, we particularly rely on the SESOI of 0.4 suggested by the review of psychological research (Brysbaert, 2019). There are various ways to quantify the statistical difference or similarity (e.g. Kullbak-Leibler divergence, Jensen-Shannon divergence, Earth mover's distance, energy distance, L_n norm, Kolmogorov-Smirnov statistic). Here we focus on effect sizes to facilitate interpretation of the magnitudes of differences.

Since our main interest lies in the identification of which features demonstrate differences or similarities between song and speech, we will perform the within-participant comparison of the six features between the pairs of singing and speech, using the spoken description rather than the lyric recitation as the proxy for speech (cf. red boxes in Fig. 3.1; the comparisons with lyrics recitation and with instrumental versions will be saved for exploratory analyses). In addition, terms in the computed difference scores will be arranged so that for our predicted differences (H1-H3), a positive value indicates a difference in the predicted direction (cf. Fig. S3).

Evaluation of difference in the magnitude of each feature is performed with nonparametric relative effects (Brunner et al., 2018) which is also known as stochastic superiority (Vargha & Delaney, 1998) or probability-based measure of effect size (Ruscio, 2008). This measure is a nonparametric two-sample statistics and allows us to investigate the statistical properties of a wide variety of data in a unified way.

We apply the meta-analysis framework to synthesize the effect size across recordings to make statistical inference for each hypothesis (Fig. 3.2). In this case, the study sample size corresponds to the number of data points of the feature in a recording and the number of studies corresponds to the number of language varieties. We use Gaussian random-effects models (Brockwell & Gordon, 2001; Liu et al., 2018), and we frame our hypotheses as the inference of the mean parameter of Gaussian random-effects models which indicates the population effect size.

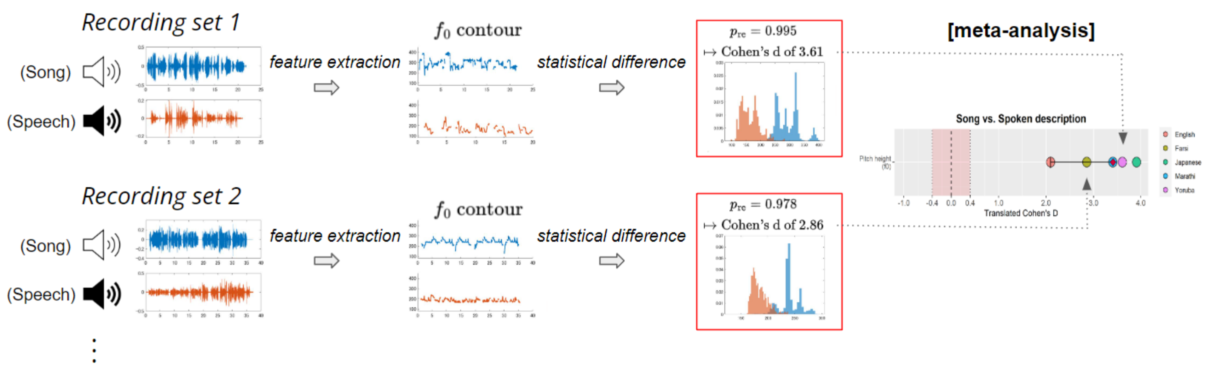


Figure 3.2. Schematic overview of the analysis pipeline from raw audio recordings to the paired comparisons shown in Figure S2. Recording sets 1 and 2 represent pilot data of singing and speaking in Yoruba and Farsi by coauthors Nweke and Hadavi, respectively. From each pair of song/spoken audio recordings by a given person, we quantify the difference using the effect size for each feature. p_{re} is the relative effect (converted to Cohen's d for ease of interpretability). In both cases, the distributions of sung and spoken pitch overlap slightly but song is substantially higher on average (Cohen's d > 2). In order to synthesize the effect sizes collected from each recording pair to test our hypotheses, we apply meta-analyses by treating each recording pair as a study. This approach allows us to make an inference about the population effect size of features in song and speech samples. This example focuses on just one feature (pitch height) applied to just two recording sets, but the same framework is applied to the other five features and other recording sets to create the processed data for hypothesis testing shown in Figure S2, Different types of hypothesis testing are applied depending on the feature (i.e. hypothesis of difference and hypothesis of similarity).

Our null hypotheses for the features predicted showing difference is that the true effect size is zero (i.e. relative effects of 0.5). On the other hand, the null hypotheses for the feature predicted showing similarity is that the true effect size is lower or larger than smallest effect sizes of interest in psychology studies (i.e. relative effects of 0.39 and 0.61 corresponding to ±0.4 of Cohen's d) (Brysbaert, 2019). We test six features, and thus test six null hypotheses.

Since we test multiple hypotheses, we will use the false discovery rate method with the Benjamini-Hochberg step-up procedure (Benjamini & Hochberg, 1995) to decide on the rejection of the null hypotheses. We define the alpha level as 0.05.

For the hypothesis testing of null effect size (H1-H3), we test whether the endpoints of the confidence interval of the mean parameter of the Gaussian random-effects model are larger than 0.5. We use the exact confidence interval proposed by Liu et al. (2018) and Wang & Tian (2018) to construct the confidence interval. For the hypothesis testing of equivalence (H4-H6), we first estimate the mean parameter (i.e. overall treatment effect) with the exact confidence interval (Liu et al., 2018; Wang & Tian, 2018) and the between-study variance with the DerSimonian-Laird estimator (DerSimonian & Laird, 1986). Since Gaussian random-effects models can be considered Gaussian mixture models having the same mean parameter, the overall variance parameter can be obtained by averaging the sum of the estimated between-study variance and the within-study variance. Then, we plug the mean parameter and overall variance into Romano's (2005) shrinking alternative parameter space method to test whether the population mean is within the SESOI as specified above.

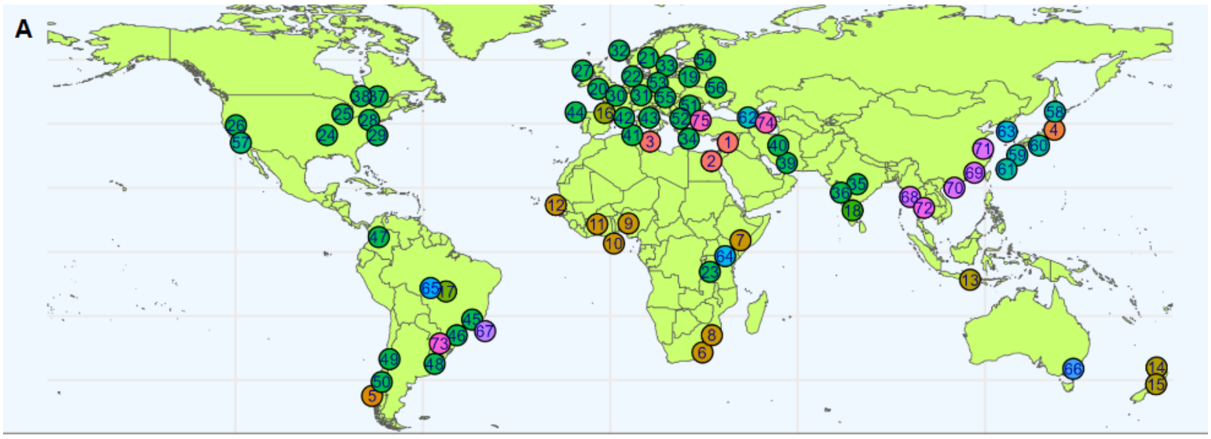
Our choice of an SESOI of d = 0.4 based on Brysbaert's (2019) recommendation after reviewing psychological studies is admittedly somewhat arbitrary. Future studies might be able to choose a different SESOI on a more principled basis based on the data and analyses we provide here, and the value of our database for such hypothesis generation and exploration is an important benefit beyond the specific confirmatory analyses proposed. However, we currently are faced with a chicken-and-egg problem in that it is difficult to justify an a priori SESOI for analysis until we have undertaken the analysis. The same argument may hold for Bayesian approaches (e.g., highest density regions, region of practical equivalence, model selection based on Bayes factors) independent of the choice of prior distributions. We thus chose to rely on Brysbaert's recommended SESOI of d = 0.4 (and its equivalent relative effect of $p_{re} = 0.61$) in the absence of better alternatives.

Visual and aural inspection of the distribution of pilot data (Figs. S2 and S9; audio recordings can be heard at https://osf.io/mzxc8/) also suggest that it is a reasonable (albeit arbitrary) threshold given the variance observed across a range of different features and languages. To enable the reader/listener to assess what an SESOI might sound like, we have created versions of the pilot data artificially raising/lowering the temporal rate and pitch height of sung/spoken examples so one can hear what our proposed SESOI would sound like for a range of languages and features (Section S7 and Table S1; audio files also at https://osf.io/mzxc8/.

3.2. Method

All details are written in the S1 Supplementary methods section. Here, we briefly introduce two key aspects: language sample and acoustic features.

We have recruited 75 collaborators from around the world, spanning the speakers of 21 language families (Fig. 3.3). All audio recordings analyzed are made by our group of 75 coauthors recording ourselves singing/speaking in our 1st/heritage languages. Collaborators were chosen by opportunistic sampling beginning from co-corresponding author Savage's network of researchers (cf. S1.2. for details).



Afro-Asiatic	Indo-European		Nilotic
1 Modern Hebrew [Jerusalem]	19 Lithuanian *Baltic*	44 Portuguese [Porto]	64 Luo (dholuo) (Luo (Kenya and Tanzania))
2 Modern Hebrew [Tel Aviv]	20 Gaeilge (Irish) *Celtic*	45 Portuguese [São Paulo]	**Nuclear-Macro-Jê**
3 Tunisian Arabic	21 Danish *Germanic*	46 Portuguese [São Paulo]	65 Rikbaktsa
Ainu	22 Dutch [Heemstede]	47 Spanish [Bogotá]	**Pama-Nyungan**
4 Aynu (Hokkaido Ainu)	23 Dutch [Nairobi]	48 Spanish [Montevideo]	66 Ngarigu
Araucanian	24 English [Indiana]	49 Spanish [Santiago]	**Puri-Coroado**
5 Tsesungún (Huilliche)	25 English [Michigan]	50 Spanish [Osorno]	67 Puri Kwaytikindo (Puri)
Atlantic-Congo	26 English [Nevada]	51 Bulgarian *Slavic*	**Sino-Tibetan**
6 IsiXhosa (Xhosa) *Bantu*	27 English [Newry]	52 Macedonian	68 Myanmar (Burmese) *Burmese-Lolo*
7 Kiswahili (Swahili)	28 English [Pennsylvania]	53 Polish	69 Cantonese (Yue Chinese) *Chinese*
8 Ronga	29 English [Washington D.C.]	54 Russian	70 HainanHua (Min Nan Chinese)
9 Yoruba *Defoid*	30 Flemish (Dutch)	55 Slovenian	71 Mandarin Chinese
10 Fante (Akan) *Tano*	31 German	56 Ukrainian	**Tai-Kadai**
11 Twi (Akan)	32 Norwegian	**Iroquoian**	72 Thai
12 Wolof *Wolof*	33 Svenska (Swedish)	57 Cherokee	**Tupian**
Austronesian	34 Greek *Greek*	**Japonic**	73 Mbyá-Guaraní
13 Balinese	35 Hindi *Indic*	58 Japanese [Hokkaido]	**Turkic**
14 Te Reo Māori (Māori) [Auckland]	36 Marathi	59 Japanese [Hyogo]	74 North Azerbaijani
15 Te Reo Māori (Māori) [Wellington]	37 Punjabi (Eastern Panjabi)	60 Japanese [Tokyo]	75 Turkish
Basque	38 Urdu	61 Northern Amami-Oshima	
16 Euskara (Basque) [Errenteria]	39 Western Farsi [Isfahan] *Iranian*	**Kartvelian**	
Cariban	40 Western Farsi [Tehran]	62 Georgian	
17 Língua Kuikuro (Kuikúro-Kalapálo)	41 Catalan *Romance*	**Koreanic**	
Dravidian	42 French	63 Korean	
18 Kannada	43 Italian		

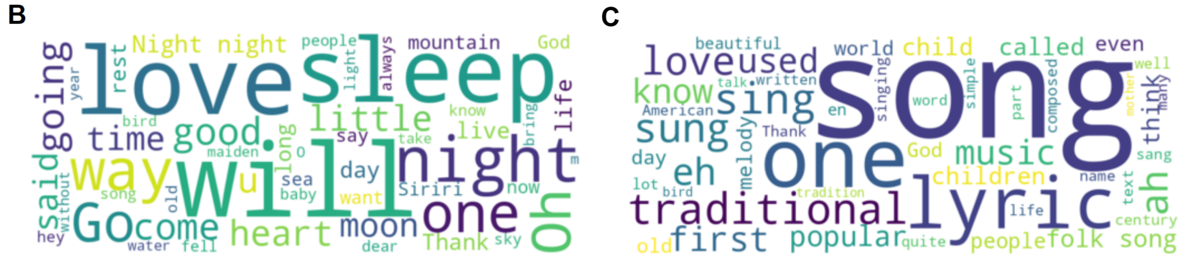


Figure 3.3. Map of the linguistic varieties spoken by our 75 coauthors as 1st/heritage languages (A). (NB: 6 of the original 81 planned coauthors were unable to complete the recording and annotation process compared to our initially planned sample; cf. Fig. S1 for the original map of 81 linguistic varieties). Each circle represents a coauthor singing and speaking in their 1st (L1) or heritage language. The geographic coordinates represent their hometown where they learned that language. In cases when the language name preferred by that coauthor (ethnonym) differs from the L1 language name in the standardized classification in the Glottolog (Hammarström et al., 2022), the ethnonym is listed first followed by the Glottolog name in round brackets. Language family classifications (in bold) are based on Glottolog. Square brackets indicate geographic locations for languages represented by more than one coauthor. Atlantic-Congo, Indo-European and Sino-Tibetan languages are further grouped by genus defined by the World Atlas of Language Structures (Dryer et al., 2013; https://wals.info/languoid). The word clouds outline the most common textual content of English translations of the song lyrics (B) and spoken descriptions (C) provided by our 75 coauthors (larger text indicates words that appear more frequently).

We compared the following six acoustic features between song and speech for our main confirmatory analyses:

1) Pitch height (fundamental frequency (f_0)) [*Hz*],
2) Temporal rate (inter-onset interval (IOI) rate) [*Hz*],
    - The unit of IOI is seconds and IOI rate is the reciprocal of IOI. Onset represents the perceptual center (P-center) of an acoustic unit (e.g., syllables, mora, note), which represents the subjective moment when the sound is perceived to begin. The P-center can be interpreted to reflect the onset of linguistic units (e.g., syllable, mora) and musical units (e.g., note), with the segmentation of acoustic units determined by the person who made the recording. This measure includes the interval between a break and the onset immediately preceding the break. Breaks were defined as relatively long pauses between sounds. For vocal recordings, that would typically constitute when the participant would inhale.
3) Pitch stability (-|f_0|) [*cent/sec.*],
4) Timbral brightness (spectral centroid) [*Hz*],
5) Pitch interval size (f_0 ratio) [*cent*],
    - Absolute value of pitch ratio converted to the cent scale.
6) Pitch declination (sign of f_0 slope) [dimensionless]
    - Sign of the coefficient of robust linear regression fitted to the phrase-wise f_0 contour.

For each feature, we compared its distribution in the song recording with its distribution in the spoken description by the same singer/speaker, converting their overall combined distributions into a single scalar measure of nonparametric standardized difference (cf. Fig. 3.2). Details can be found in S1.3. and S3.

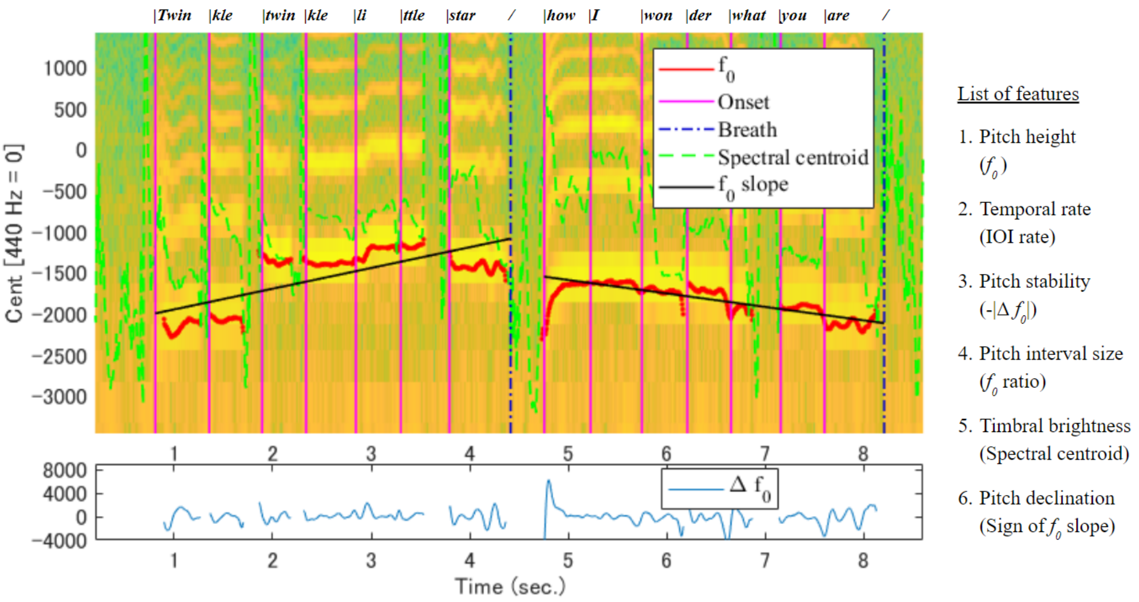


Figure 3.4. Schematic illustration of the six features analyzed for confirmatory analysis, using a recording of author Savage singing the first two phrases of "Twinkle Twinkle Little Star" as an example. Onset and breathing annotations are based on the segmented texts displayed on the top of the spectrogram. The y-axis is adjusted to emphasize the f_0 contour, so note that the spectral centroid information is not fully captured (e.g. high spectral centroid due to the consonant). The

bottom figure shows pitch stability (rate of change of f_0, or derivative of the f_0 contour equivalently) of the sung f_0.

Changes to Stage 1 Registered Report protocol (Introduction and Method sections 1-2 plus Supplementary Materials)

We have left the content of Introduction and Method (Sections 1-2) and Supplementary Materials unchanged from the version granted In Principle Acceptance (accessible at https://osf.io/download/6387919ba98e5f286310370d/?version=4), following Registered Report procedures to avoid any possibility of adjusting hypotheses or analyses after knowing the results. However, we have moved the majority of the Method section to Supplementary Materials to make the main result and discussion easier to read. At the time we submitted the Stage 1 manuscript, we mainly reported our pilot data results included in the Method section, but now those results have been moved to Supplementary Information.

As a result, we have renumbered Section and Figure numbers and have updated cross-references to them. In addition, we have added a subsection title to the paragraph explaining exploratory features in the supplementary materials which should have been there. Minor typos have also been corrected accordingly.

Note that the map in the Methods section (Fig. 3.3) reflects the final 75 collaborators who provided audio recording data, not the original 81 collaborators shown in the original map (Fig. S1), as 6 collaborators were unable to provide recording data. We have also added a word cloud visualization of the translated content of the sung/spoken audio recordings to accompany this map.

3.3. Results

3.4.2 Confirmatory analysis

The results of the confirmatory hypothesis testing with 73 recording sets confirm 5 of our 6 predictions (Fig. 3.5 and Table 2; all $p < 1x10^{-5}$). Specifically, relative to spoken descriptions, songs used significantly higher pitch (translated Cohen's D = 1.6), slower temporal rate (D = 1.6), and more stable pitches (D = 0.7), while both spoken descriptions and songs used significantly equivalent timbral brightness and pitch interval size (both D < 0.15). The one exception was pitch declination, which was not significantly equivalent between speech and song (p=.57), with an estimated effect size of D = 0.42 slightly greater than our pre-specified "Smallest Effect Size of Interest" (SESOI) of D = 0.4. In section 4.2.7 we perform alternative exploratory analyses to understand possible reasons for this failed prediction.

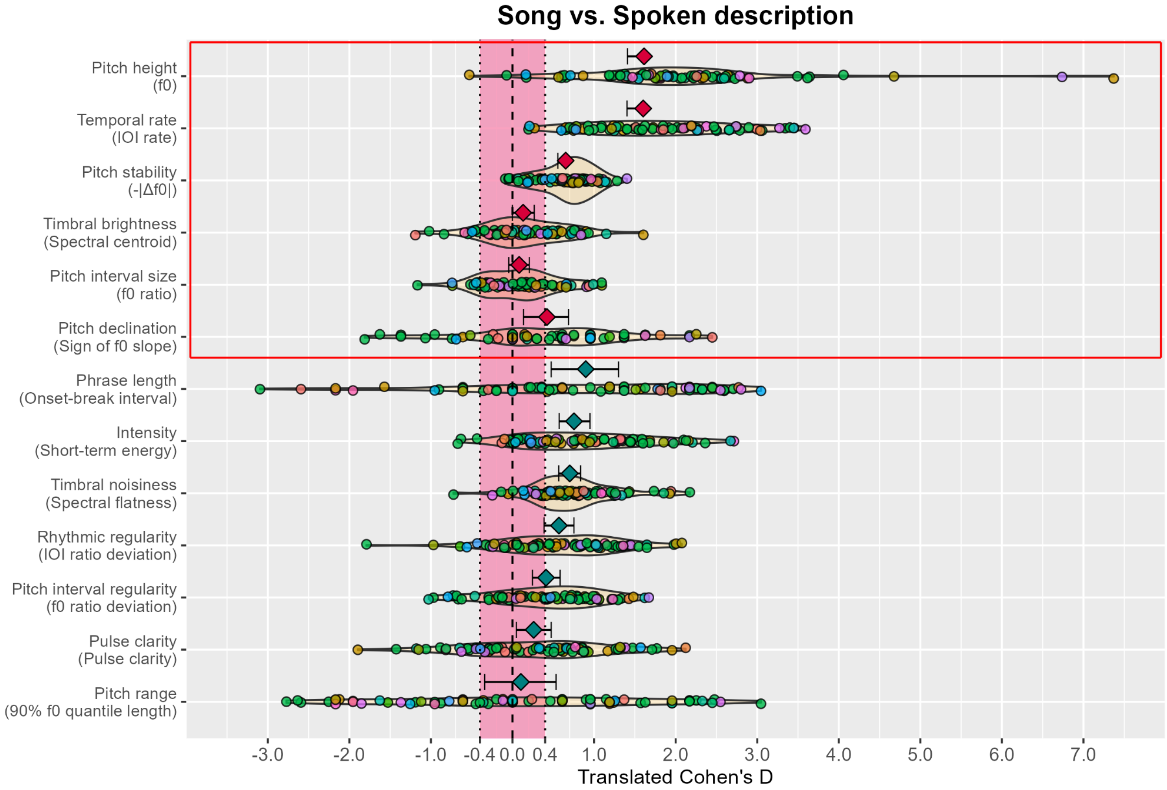


Figure 3.5. Plot of effect sizes showing differences of each feature between singing and spoken description of the 73 recording sets for the confirmatory analysis and 75 recording sets for the exploratory analysis. The plot includes 7 additional exploratory features, and the 6 features corresponding to the main confirmatory hypotheses are enclosed by the red rectangle. Confidence intervals are created using the same criteria in the confirmatory analysis (i.e., α = 0.05/6). Each circle represents the effect size from each recording pair of singing and spoken description, and the set of effect sizes are measured per recording pair. Readers can find further information on how to interpret the figure in the caption of Figure S2 and Figure S9. Note that the colors of data points indicate language families, which are coded the same as in Figure 3.3, and violin plots are added to this figure compared to Figure S2.

Hypothesis	Feature	Test	Combined ES	CI (α = 0.05/6)	p-value
1) Song uses higher pitch than speech	f_0	One-tailed confidence interval of the combined effect size	1.61	1.41, n/a	*< 1.0x10^{-8}
2) Song is slower than speech	IOI rate		1.60	1.40, n/a	*< 1.0x10^{-8}
3) Song uses more stable pitches than speech	$-\|\Delta f_0\|$		0.65	0.56, n/a	*< 1.0x10^{-8}
4) Song and speech use similar timbral brightness	Spectral centroid	Equivalence test for the combined effect size	0.13	-0.0046, 0.27	*5.2x10^{-6}
5) Song and speech use similar sized pitch intervals	f_0 ratio		0.082	-0.044, 0.21	*< 1.0x10^{-8}
6) Song and speech use similar pitch contours	Sign of f_0 slope		0.42	0.13, 0.69	.57

Table 3.2. Results of the confirmatory analysis. The effect sizes reported in the table are Cohen's *d* transformed from relative effects for ease of interpretation, but the hypothesis tests were conducted with relative effects. The CIs are either one-tailed or two-tailed, depending on the aim of the test. Note the equivalence test uses statistics different from the above meta-analysis CIs to verify equivalence hypotheses. Asterisks in p-values indicate that the null hypothesis is rejected.

Our robustness checks confirmed that the tests with the recordings excluding collaborators who knew the hypotheses when generating data lead to the same decisions regarding the rejection of the null hypotheses (Table 3). This result suggests our unusual "participants as coauthors" model did not influence our confirmatory analyses. In addition, the other robustness check suggests that the measured effect sizes do not have language family-specific variance (Table 4), which supports the appropriateness of the use of simple random-effect models in the analyses.

Hypothesis	Feature	Test	Combined ES	CI (α = 0.05/6)	p-value
1) Song uses higher pitch than speech	f_0	One-tailed confidence interval of the combined effect size	1.73	1.46, n/a	**$*< 1.0x10^{-8}$**
2) Song is slower than speech	IOI rate		1.64	1.40, n/a	**$*< 1.0x10^{-8}$**
3) Song uses more stable pitches than speech	$-\|\Delta f_0\|$		0.64	0.51, n/a	**$*< 1.0x10^{-8}$**
4) Song and speech use similar timbral brightness	Spectral centroid	Equivalence test for the combined effect size	0.14	-0.028, 0.31	**$*3.3x10^{-4}$**
5) Song and speech use similar sized pitch intervals	f_0 ratio		0.10	-0.067, 0.27	**$*3.5x10^{-5}$**
6) Song and speech use similar pitch contours	Sign of f_0 slope		0.23	-0.11, 0.60	.12

Table 3.3. Results of the robustness check, which used data only from the collaborators who had not known the hypotheses when generating data (47 pairs of singing and spoken description recordings).

Hypothesis	AIC (standard)	AIC (multi-level)	Log likelihood (standard)	Log likelihood (multi-level)	Variance of the effects at language family
1) Song uses higher pitch than speech	**-87.08**	-85.08	45.54	45.54	$< 1.0\times10^{-8}$
2) Song is slower than speech	**-111.64**	-109.73	57.82	57.86	1.86×10^{-3}
3) Song uses more stable pitches than speech	**-153.53**	-151.53	78.76	78.76	$< 1.0\times10^{-8}$
4) Song and speech use similar timbral brightness	**-86.32**	-84.90	45.16	45.45	2.07×10^{-3}
5) Song and speech use similar sized pitch intervals	**-95.90**	-93.90	49.95	49.95	$< 1.0\times10^{-8}$
6) Song and speech use similar pitch contours	**-7.24**	-5.48	5.62	5.74	2.29×10^{-3}

Table 3.4. Results of the robustness check comparing models taking into account dependency by language families. Superior AIC scores are highlighted in bold. Maximum likelihood estimation is used to fit the models. “standard” refers to standard random-effects models used in the confirmatory analyses, and “multi-level” refers to two-level random-effects models grouping data by language families. The right-most column shows the maximum likelihood estimate of the variance parameters appearing in the multi-level models. The log-likelihoods are almost identical between the two models, and multi-level models degenerate to standard random effects models (i.e. variance due to language family is negligible), which means grouping data by language family is redundant and simple random effects models are enough to model data.

3.4.2.1 More acoustic features

We specified six features for our confirmatory analyses, but human music and speech can be characterized by additional acoustic features. We include seven additional features to probe further similar and different aspects of music and speech, namely rhythmic regularity, phrase length (duration between two breaths/breaks), pitch interval regularity, pitch range, intensity, pulse clarity, and timbral noisiness (cf. section S6). Although we do not formally construct and test hypotheses for this analysis, Figure 3.5 suggests that phrase length, intensity, and timbral noisiness may also inform differences between song and speech, and pitch range can be another candidate for demonstrating similarities between song and speech. Specifically, songs appear to have longer intervals between breathing, higher sound pressure, and have less vocal noise than speech. Note that as described in 1.2, the order of comparison is arranged so that difference is expressed as a positive value, so that difference in timbral noisiness is calculated as noisiness of spoken description relative to song.

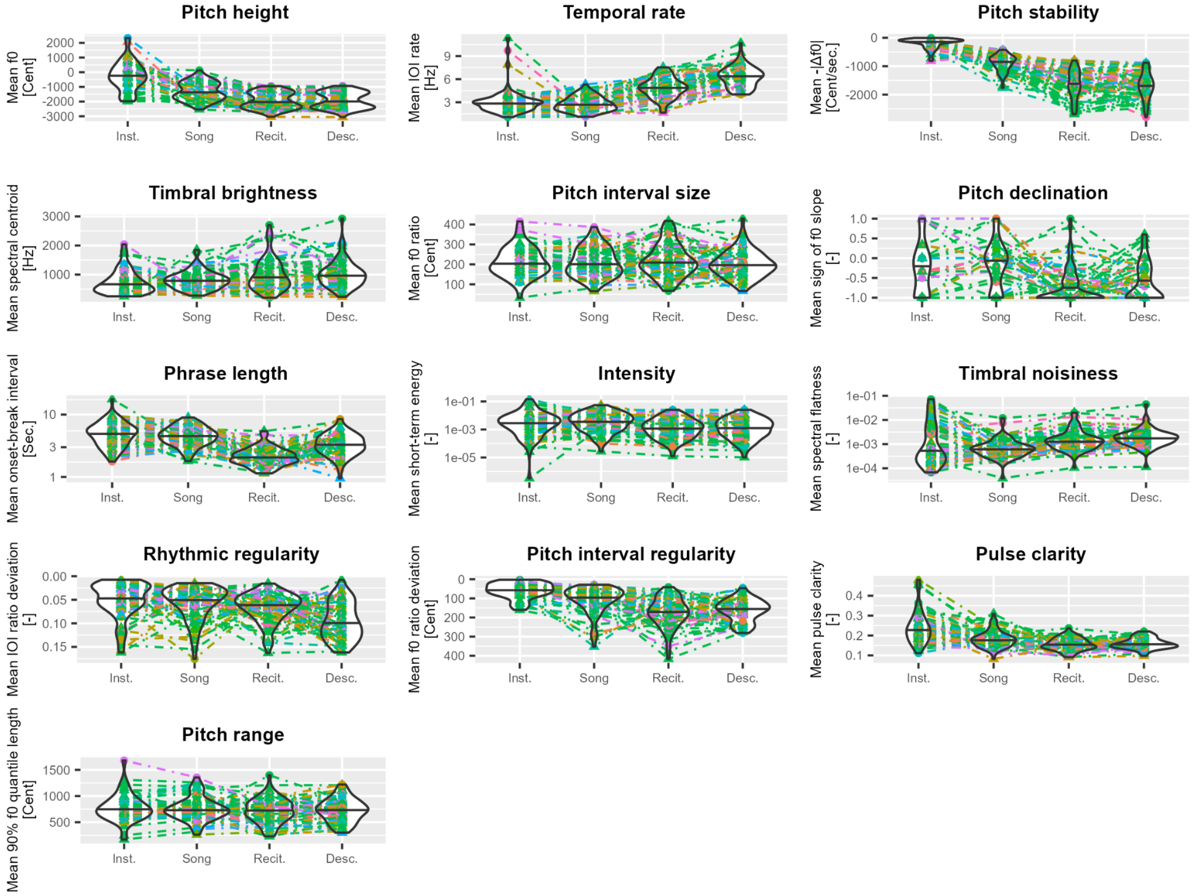


Figure 3.6. Alternative visualization of Figure 3.5 showing mean values of each feature rather than paired differences but with all recording types. Note that the colors of data points indicate language families, which are coded the same as in Figure 3.3. The horizontal lines in the violin plots indicate the median.

3.4.2.2 Music-language continuum: including instrumental/recited lyrics

Exploratory analyses that include comparisons with lyrics recitation and instrumental recordings (cf. Fig. S13 and Fig. 3.6) suggest that 1) comparing singing vs. lyrics recitation shows qualitatively the same results as for singing vs. spoken description in terms of how confidence intervals intersect with the null point and the equivalence region; 2) comparing instrumental vs. speech (both spoken description/lyrics recitation) reveals larger differences in pitch height, temporal rate, and pitch stability than found with song vs. speech; 3) features shown to be similar between song vs. speech (e.g., timbral brightness and pitch interval size) show differences when comparing instrumental vs. speech; 4) few major differences are observed between lyrics recitation and spoken description, except that recitation tends be slower and use shorter phrases; 5) the instrumental generally has a more extreme (larger/smaller) magnitude than singing for each feature except for temporal rate; and 6) pitch height, temporal rate, and pitch stability display a noticeable constantly increasing (or decreasing) continuum from spoken description to instrumental.

A similar trend is also found in additional differentiating features discussed in 4.2.1 (i.e., phrase length, timbral noisiness, and loudness). We also performed a nonparametric trend test (cf., Table S2) to quantitatively assess the existence of trends, and the result suggests that features other than pitch interval size and pitch range display increasing/decreasing trends. These results tell us how acoustic characteristics are manipulated through the range of acoustic communication from spoken language to instrumental music.

3.4.2.3 Demographic factors: Sex differences in features

Because we had a similar balance of female (n=34) and male (n=41) coauthors, we were able to perform exploratory analysis comparing male and female vocalizations (Fig. S14). These analyses suggest that, while there is some overlap in their distribution (e.g., some male speaking/singing was higher than some female speaking/singing), on average female vocalizations were consistently higher-pitched than male vocalizations regardless of the language sung/spoken (by ~1,000 cents [almost one octave] consistently for song, spoken description, and recited lyrics). However, there is no apparent sexual dimorphism in vocal features other than pitch height (e.g., temporal rate, pitch stability, timbral brightness, etc.). Although this analysis is exploratory, this result is consistent with past research that often focuses on vocal pitch as a likely target of sexual selection (Chen et al., 2022; Feinberg et al., 2018; Puts et al., 2006; 2016; Valentova et al., 2019).

3.4.2.4 Analysis by linguistic factors: nPVI

We employed nPVI (Patel & Daniele, 2003) to examine the degree of variation in inter-onset intervals and onset-break intervals (cf. S3.2. & S8.) of our song and speech recordings. nPVI provides large values if adjacent intervals differ in duration on average and vice versa. Thus, nPVI can capture durational contrasts between successive elements. It was originally developed to characterize vowel duration of stress-timed and syllable-timed languages (Ling et al., 2000), although our duration is defined by the sequence of onset (cf. S1.1.) and break annotations (cf. S8.) which are neither the same as vowel duration nor vocalic intervals. In this exploratory analysis, we mapped nPVIs of song and spoken description recordings of each collaborator on a two-dimensional space to explore potential patterns and also visualized the density of nPVIs per recording type (cf. Fig. S20). However, we observed that (1) nPVIs of song and spoken description do not seem to create distinct clusters among our recordings (whether into “syllable-timed”, “stress-timed”, or any other categories), (2) nPVIs of song and spoken description do not have a clear correlation (Pearson's *r* = 0.087) while nPVIs of song and instrumental recording do show a substantial correlation (Pearson's *r* = 0.52), and (3) nPVIs of spoken description tend to be slightly larger than song and instrumental. The third result suggests durational contrast of speech is more variable compared to singing and instrumental, which is consistent with past work showing that music tends to have limited durational variability worldwide (Savage et al., 2015). In addition, though linguists use various features (Grabe & Low, 2002) to carefully characterize the rhythm of speech, the first two observations suggest that song rhythm is potentially independent of speech rhythm even when produced by the same speaker in the same language, which suggests that temporal control of song and speech may obey different communicative principles.

3.4.2.5 Reliability of annotation process: Inter-rater reliability of onset annotations

We analyzed the inter-rater reliability of onset annotations to check how large individual varieties are in the annotation. As stipulated in S1.7.7, Savage created onset annotations to the first 10 seconds of randomly chosen 8 pairs of song and spoken description recordings. In this 10-second annotation, Savage created onset annotations using the same segmented text as Ozaki (the text provided by the coauthor who made the recording) but was blinded from the actual annotation created by YO and confirmed by the coauthor who made the recording. Therefore, the annotation by PES follows the same segmentation as the annotation by YO, but can differ in the exact timing for which each segmentation is judged to begin. We measured intra-class correlations (ICCs) of onset times with two-way random-effects models measuring absolute agreement. As a result, all annotations show strong ICCs (> .99), which indicates who performs the annotation may not matter as long as they strictly follow the segmentation indicated in segmented texts. Alternative exploratory analysis inspecting the distribution of differences in onset times is also conducted (cf., Fig. S21). In the case of singing, 90% of onset time differences are within 0.083 seconds. Similarly, in the case of spoken description, 90% of onset time differences are within 0.055 seconds. In other words, Ozaki's manual onset annotations that form a core part of our dataset have been confirmed by the coauthor who produced each recording and by Savage's independent blind codings to be highly accurate and reliable.

4.2.6. Exploring recording representativeness and automated scalability: Comparison with alternative speech-song dataset (Hilton et al., 2022)

As stated in S1.7.8, we performed two exploratory analyses using automated methods to investigate (1) the reproducibility of our findings with another corpus and (2) the applicability of automated methods to substitute data extraction processes involving manual work. We analyzed the recordings of adult-directed singing and speech of Hilton et al.'s (2022) dataset. We especially analyzed both the full set of their data and the subset of their data representing languages also present in our own dataset - English, Spanish, Mandarin, Kannada, and Polish - to perform a matched comparison with our language varieties. However, in their dataset, not all individuals made a complete set of recordings (infant/adult-directed song/speech), and we analyzed recording sets containing matching adult-directed song and adult-directed speech recordings, which resulted in 209 individuals for the full data (i.e., individuals from full 21 societies/16 languages) and 122 individuals for the above subset of 5 languages.

Our data extraction processes involving manual work are fundamental frequency extraction, sound onset annotation, and sound break annotation, and we automated fundamental frequency extraction since reliable fundamental frequency estimators applicable to both song and speech signals are readily available. On the other hand, reliable automated onset and break annotation for both song and speech is still challenging. For example, we observed that a widely used syllable nuclei segmentation method by de Jong & Wempe (2009) failed to capture the major differences in temporal rate that we identified using manual segmentation in Fig. 3.5. Instead, if we had used this automated method, we would have mistakenly concluded that there is no meaningful difference in IOI rates of singing and speech (Fig. S15). Therefore, as described in our Stage 1 protocol, we only focused on the automation of f_0 extraction that could provide reliable results even using purely automated methods without requiring manual annotations.

We chose the pYIN (Mauch & Dixon, 2014) f_0 extraction algorithm for this analysis. In addition, we analyzed full-length recordings by taking advantage of the efficiency of automated methods. Note that our timbral brightness analysis is already fully automated, so we use the same analysis procedure for this feature. The result suggests that (1) the same statistical significance can be obtained from Hilton et al.'s data though overall effect sizes tend to be weakened, and (2) combined effect sizes based on pYIN with full-length duration only show negligible differences from the original analysis involving manual work despite the drastic difference in the measurement of some effect sizes (i.e., no effect sizes larger than 3.5 in the automated analysis of the pitch height of our data). Note that the differences in pitch stability in Hilton et al.'s sample (translated Cohen's d=0.30) are small enough to be within our defined equivalence region (|d|<0.4) if we had predicted it to be equivalent, but it is also significantly greater than the null hypothesis of no difference (translated Cohen's d=0 corresponding to relative effect of 0.5), as we predicted (p < .005). Similar to Fig. 3.6, mean values of each feature per recording can be found in the supplementary information (Fig. S17-S19).

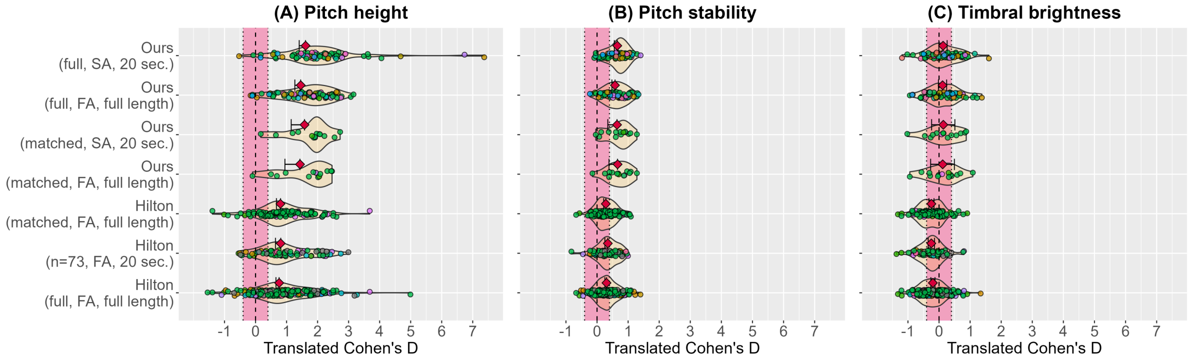


Figure 3.7. Re-running the analyses on four different samples using different fundamental frequency extraction methods: 1) our full sample (matched song and speech recordings from our 75 coauthors); 2) Hilton et al.'s (2022) full sample (matched song and speech recordings from 209 individuals); 3) a sub–sample of our 14 coauthors singing/speaking in English, Spanish, Mandarin, Kannada, and Polish), and 4) a sub-sample of Hilton et al.'s 122 participants also singing/speaking in English, Spanish, Mandarin, Kannada, and Polish). "SA" means that f_0s are extracted in a semi-automated manner (cf. S3.1), while "FA" means they were exactly in a fully automated manner (using the pYIN algorithm). Semi-automated analyses could only be performed on 20s excerpts of our recordings annotated by the coauthor who recorded them, while automated analyses could be applied to the full samples. In order to make the comparison with our results more interpretable, we have also added the analysis of Hilton's data using the same number of song-speech recording pairs with us (i.e., randomly selected 74 pairs of recordings), extracting features from the first 20 seconds. Since temporal rate, pitch interval size, and pitch declination analyses require onset and break annotations, we focused on pitch height, pitch stability, and timbral brightness. The visualization follows the same convention as in Figure 3.5 and Figure 3.8. However, Hilton et al.'s (2022) dataset contains languages that are not in our dataset. Therefore, slightly different color mapping was applied (cf. Fig. S16). Note that some large effect sizes (D > 3.5) in the pitch height of our original analysis (i.e., full-SA-20 sec.) are not observed in the automated analysis (i.e., full-FA-full length). This is due to estimation errors in the automated analyses. When erroneous f_0s of pYIN are very high in spoken description or very low in singing, relative effects become smaller than semi-automated methods that remove such errors.

4.2.7. Alternative analysis approaches for pitch declination (hypothesis 6)

The only one of our 6 predictions that was not confirmed was our prediction that song and speech would display similar pitch declination. However, we would like to point out that only 3 to 4 f_0 slopes (equal to the number of "phrases" or intervals from the first onset after a break and to the next break, cf. Fig. 3.4) are, on average, included in the 20s length recording of singing and spoken description, respectively, and so it is possible that this failed prediction could be due to the relatively more limited amount of data available for this feature. Therefore, we additionally checked the validity of the result of this hypothesis test using a longer duration to extract more signs of f_0 slopes to evaluate effect sizes. Although we performed exploratory reanalysis using 30s recordings which contain 5 to 7 f_0 slopes for singing and spoken description on average, still the p-value was not small enough to reject the null hypothesis (p = .48, CI [.17, .60]).

Note that we are judging the declination in an f_0 contour by looking at the sign of the slope of linear regression (i.e., the sign is negative means declination). Therefore, even if the f_0 contour is an arch shape, which means it has a descending contour at the end part, it can be judged as no declination if the linear regression shows a positive slope. Therefore, the declination here means if the f_0 contour has a descending trend overall and not necessarily if the phrase is ending in a downward direction.

We report here an additional analysis based on a different approach for handling the case when signs of f_0 slopes are not directly analyzable. Some singing and spoken description recording pairs only contained negative signs (i.e. descending trend prosody). This is undesirable for inverse variance-weighted based meta-analysis methods which we use (e.g. DerSimonian-Laird estimator) since the standard deviations of effect sizes become zero, leading to computation undefined. We employed the same procedure used in our power analysis for such cases (cf. S4.2), but a more widely known practice would be zero-cell corrections used in binary outcome data analysis (Weber et al., 2020). Signs of f_0 slopes are dichotomous outcomes (i.e. positive or negative), and drawing upon zero-cell corrections, we artificially appended a plus and minus sign to each of the signs of f_0 slopes from singing and spoken description recordings when estimating standard errors of relative effects if needed (e.g. [-1, -1, -1] → [-1, -1, -1, 1, -1] for the case of 3 f_0 slopes). In zero-cell corrections, 0.5 is added to all cells of the 2×2 table. Our analysis is not based on count data, so we cannot exactly follow this correction. However, adding plus and minus signs to the outcome of both singing and spoken description recordings has a similar effect. In other words, our additional procedure is similar to zero-cell corrections but adding 1 instead of 0.5 to all cells. This additional analysis provided virtually identical results with the main analysis reported in 3.1 (p = .66, CI [.15, .71]), suggesting that the way to handle zero frequency f_0 slope sign data is not crucial.

Lastly, we also checked the average trend of f_0 contours segmented by onset and break annotations (cf. Figure 3.8). The averaged f_0 contour of spoken description recordings clearly exhibits a predominantly descending trend, albeit with a slight rise at the end. In contrast, the averaged f_0 contour of songs is close to an arch shape, so that even though the second half of songs tend to descend as predicted, the first half of songs tend to rise, in contrast to speech which tends to mostly descend throughout the course of a breath. Thus, on average spoken pitch contours tend to descend more than sung pitch contours, explaining our failure to confirm our prediction that their contours would display similar pitch declination (cf. Fig. 3.5). We also noticed that vocalizers sometimes end their utterance by raising pitch in their spoken description recordings (and lyrics recitation as well), causing a slight rise at the end of the averaged f_0 contour of spoken description (and lyrics recitation, cf. Figure 3.8).

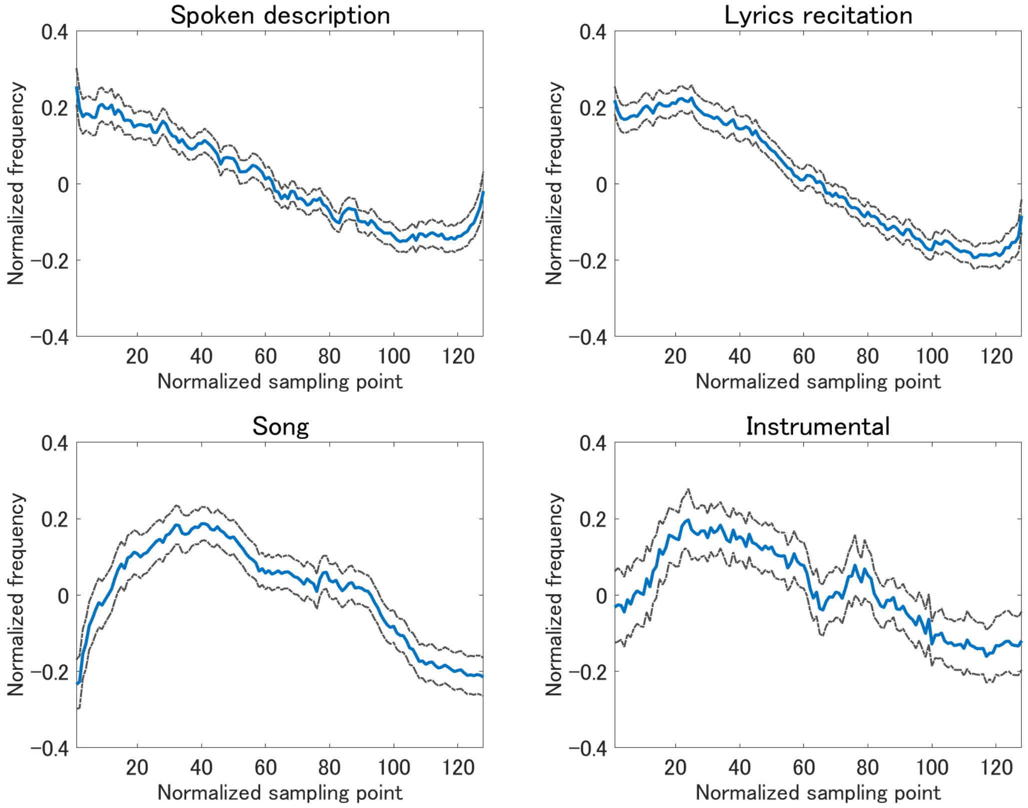


Figure 3.8. Averaged *f_0* contours. *f_0* contours extracted by the segments between onset and break were averaged to visualize the overall trend. The extracted *f_0* contours were normalized to the length of 512 samples using interpolation by Fourier transform and resampling (Fraser, 1989; Schafer & Rabiner, 1973). The implementation by the MATLAB function interpft is used. Besides, the frequencies of extracted *f_0* contours were standardized. Missing data from unvoiced segments of f0 contours were excluded. The blue lines represent averaged *f_0* contours, and the black lines indicate 95% confidence intervals assuming the frequencies at each normalized sampling point were distributed normally. The average widths of confidence intervals of each category are .14 for instrumental, .097 for song, .060 for lyrics recitation, and .065 for spoken description.

Furthermore, the width of standard errors around the mean contour (cf. Figure. 3.8) suggests that spoken description and lyrics recitation have more homogeneous variations of contours than song and instrumental. This difference may corroborate that music actually makes more use of the manipulation of the pitch in communication. Indeed, musical melodies are considered to have multiple typical shapes (Adams, 1976), so the overall average contour is not necessarily representative of all samples.

3.4.2.8. Explanatory power of the features in song-speech classification

In order to probe the explanatory power of features on classifying acoustic signals into song and speech, we evaluated feature importance using permutation importance (Breiman, 2001) with three simple machine learning models. Permutation importance informs the influence on the machine learning model by a particular variable by randomly shuffling the data of the variable (e.g., imagine a data matrix that row corresponds to observations and column corresponds to variables, and the data in a particular column are shuffled). Here we use the permutation importance, which is the version implemented in Python's eli5 package

(*Permutation Importance*, n.d.). Since how the feature contributes to solving the given task differs in machine learning models, we employed three binary classification models to mitigate the bias from particular models: logistic regression with L2 regularization, SVM with RBF kernel, and naive Bayes with Laplace smoothing.

We computed permutation importance by randomly splitting 75 recording sets into the training set (n = 67) and test set (n = 8, 10% held-out) to fit the model and to evaluate the importance of features in the classification task, and repeated the same process 1024 times. The mean values of the feature, which are plotted in Figure 3.6, were used as data after normalization. The average of 1024 realizations of permutation importance values was reported here as the final output.

The result suggests at least temporal rate, pitch stability, and pitch declination are constantly weighed among these three models (cf. Fig. S22). All classifiers achieved average accuracy and F1 score higher than 90 (cf. Table S3). The importance of the other features depends on the models. For example, logistic regression gave the highest importance to pitch interval regularity as their 3rd most important feature. Naive Bayes chose rhythmic regularity as the 2nd most important feature, but this feature did not have a noticeable impact on SVM. On the other hand, it is consistent with the confirmatory analysis that pitch interval size and timbral brightness are evaluated as unimportant in discriminating between song and speech.

Interestingly, there are several cases that some features showing a strong difference within subjects were not evaluated as important in this analysis, including pitch height and intensity (cf. Fig. 3.5 and Fig. S22). Two reasons can be considered. One reason is relative largeness within the individual is not as informative in classifying acoustic signals collected from multiple individuals. In this case, between-subjects consistent differences would be more informative. Another scenario is that there is an overlap in information among features. Correlation matrices of the features within song and speech (cf. Fig. S23-S24) show several features have medium to large size correlation (e.g., increase in pitch interval regularity with a decrease in temporal rate in singing with r = -.53). Therefore, there is a possibility that some features are evaluated as unimportant not because that feature is irrelevant to classify song and speech but because the information in that feature overlaps with other features. This comes from the limitation of permutation importance that this measurement does not take into account correlation among features.

Inspection of the correlation matrices suggests complex interactions exist among features. Although what is captured in correlation matrices is a linear dependency between two variables, nonlinear dependency among features or dependency among more than two variables can also happen in vocal sound production. However, correlation is considered acting in the underestimation of permutation importance (Pereira et al., 2022). Therefore, at least the two features that consistently scored high among the three between-participant models and that confirmed our predicted within-participant differences - namely, temporal rate and pitch stability - capture important factors differentiating song and speech across cultures.

3.5 Discussion

3.5.1. Main confirmatory predictions and their robustness

Our analyses strongly support five out of our six predictions across an unprecedentedly diverse global sample of music/speech recordings: 1) song uses higher pitch than speech, 2) song is slower than speech, 3) song uses more stable pitches than speech, 4) song and speech use similar timbral brightness, and 5) song and speech use similar sized pitch intervals (Fig. 3.5). Furthermore, the first three features display a shift of distribution along the musi-linguistic continuum, with instrumental melodies tending to use even higher and more stable pitches than song, and lyric recitation tending to fall in between conversational speech and song (Fig. 3.6).

While some of our findings were already expected from previous studies mainly focused on English and other Indo-European languages (Chang et al., 2022; Ding et al., 2017; Hansen et al., 2020; Merrill & Larrouy-Maestri, 2017; Sharma et al., 2021; see also S2.1 and Blasi et al., 2022), our results provide the strongest evidence to date for the existence of "statistically universal" relationships between music and speech across the globe. However, none of these features can be considered an "absolute" universal that *always* applies to all music/speech. Fig. 3.5 shows many exceptions for four of the five features: for example, Parselelo (Kiswahili speaker) sang with a lower pitch than he spoke, and Ozaki (Japanese speaker) used slightly more stable pitches when speaking than singing, while many recording sets had examples where differences in sung vs. spoken timbre or interval size were substantially larger than our designated "Smallest Effect Size Of Interest". The most consistent differences were found for temporal rate, as song was slower than speech for all 73 recording sets in our sample. However, additional exploratory recordings have revealed examples where song can be faster than speech (e.g., Savage performing Eminem's rap from "Forgot About Dre" [https://osf.io/ba3ht]; Parselelo's recording of traditional *Moran* singing by Ole Manyas, a member of Parselelo's ancestral Maasai community [https://osf.io/mfsjz]).

Our sixth prediction - that song and speech use similar pitch contours - remained inconclusive. Instead of our predicted similarities, our exploratory analyses suggest that, while both song and speech contours tend to decline toward the *end* of a breath, they tend to do so in different ways: song first rising before falling to end near the same height as the beginning, speech first descending before briefly rising at the end (Fig. 3.8). Our prediction was based in part on past studies by some of us finding similar pitch contours in human and bird song, which we argued supported a motor constraint hypothesis (Tierney et al., 2011; Savage et al., 2017). However, our current results suggest that motor constraints alone may not be enough to explain similarities and differences between human speech, human song, and animal song, and that future studies directly comparing all three domains will be needed.

Our robustness checks confirm that our primary confirmatory results were not artefacts of our choice to record from a non-representative sample of coauthors. Specifically: 1) language families do not account for variances in the measured song-speech differences and similarities (Table 4), which means that these differences and similarities are cross-linguistically regular phenomena, and 2) analyzing only recordings from coauthors who made recordings prior to learning our hypotheses produced qualitatively identical conclusions (Table 3). Analysis of Hilton et al.'s (2022) dataset of field recordings also supplemented our findings, producing qualitatively identical conclusions, regardless of the precise analysis methods or specific sample/sub-sample used (Fig. 3.7).

3.5.2. Implications from the exploratory analyses

Comparisons with lyrics recitation and instrumental recordings revealed the relationship between music and language can noticeably change depending on the type of acoustic signal. In general, many features followed the predicted "musi-linguistic continuum" with instrumental music and spoken conversation most extreme (e.g., most/least stable pitches respectively), with song and lyric recitation occupying intermediate positions (Fig. 3.6). However, for temporal rate, songs were more extreme (slower) than instrumental music, while for phrase length, lyric recitation was more extreme (shorter) than spoken conversation. Increasing variations of acoustic signals and designing the continuum with multiple dimensions (e.g., by adding further categories such as infant-directed song/speech, or speech intended for stage acting; mapping music and language according to pitch, rhythm, and propositional/emotional functionality) may elucidate a more nuanced spectrum of musi-linguistic continuum (Brown, 2000; Leongómez et al., 2022; Hilton et al., 2022).

3.5.3. Limitations on generality

A limitation of our study is that, because our paradigm was focused on isolating melodic and lyrical components of song, the instrumental melodies we analyzed are not representative of all instrumental music but only instrumental performance of melodies intended to be sung. It is thus possible that instrumental music intended for other contexts may display different trends (e.g., music to accompany dancing might be faster). Different instruments are also subject to different production constraints, some of which may be shared with singing and speech (e.g., aerophones like flutes also are limited by breathing capacity), and some of which are not (e.g., chordophones like violins are limited by finger motor control). For example, though most of our instrumental recordings followed the same rhythmic pattern of the sung melody, Dessiatnitchenko's instrumental performance on the Azerbaijani *tar* was several times faster than her sung version because the *tar* requires the performer to repeatedly strum the same note many times to produce the equivalent of a single long sustained note when singing (listen to her instrumental recording at https://osf.io/uj3dn).

Another limitation of our instrumental results is that, while none of our collaborators reported any difficulty or unnaturalness in recording a song and then recording a recited version of the same lyrics, many found it unnatural to perform an instrumental version of the sung melody. For example, while the Aynu of Japan do use pitched instruments such as the *tonkori,* they are traditionally never used to mimic vocal melodies. In order to compare sung and instrumental features, all of our collaborators agreed to at least record themselves tapping the rhythm of their singing, but such recordings without comparable pitch information (n=28 recordings) had to be excluded from our exploratory analysis of pitch features, and even their rhythmic features may not necessarily be representative of the kinds of rhythms that might be found in purely instrumental music. Likewise, the conversational speech recorded here is not necessarily representative of non-spoken forms of language (e.g., sign language, written language).

3.5.4. Comparison with alternative dataset (Hilton & Moser et al., 2022)

Interestingly, while the qualitative results using Hilton et al.’s dataset were identical, the magnitude of their song-speech differences were noticeably smaller. For example, while song was substantially higher-pitched than speech in both datasets, the differences were approximately twice as large in our dataset as in Hilton et al.’s (~600 cents [half an octave] on average vs. ~300 cents [quarter octave], respectively). These differences were consistent even when analyzed using matching sub-samples speaking the same languages and using the same fully automated analysis methods (Fig. 3.7), suggesting they are not due to differences in the sample of languages or analysis methods we chose.

Instead, we speculate that these differences may be related to differences in recording context and participant recruitment. While our recordings were made by each coauthor recording themselves in a quiet, isolated environment, Hilton et al.’s recordings were field recordings designed to capture differences between infant-directed and adult-directed vocalizations, and thus contain various background sounds other than the vocalizer’s speaking/singing (especially high-pitched vocalizations by their accompanying infants; cf. Fig. S11).Such background noise may reduce the observed differences between speech and song.

Another potential factor is musical experiences. Our coauthors were mostly recruited from academic societies studying music, and many also have substantial experience as performing musicians. Although the degree of musical experiences of Hilton et al.’s participants is not clear, the musical training of our participants is likely more extensive than a group of people randomly chosen from general populations. Such relatively greater musical training may have influenced the production of higher and more stable pitches in singing. In fact, we confirmed that there is no obvious difference in pitch stability of speech between ours and Hilton et al.’s dataset (2022), but our singing recordings have higher stability than theirs (Fig. S18). Similarly, even if pitch estimation errors due to background noise erroneously inflated estimated f_0 of Hilton et al.’s recordings due to noise, our singing showcased the use of more heightened pitch (Fig. S17).

Interestingly, we also observed that our spoken recordings have slightly lower pitch height than Hilton et al.'s spoken recordings. Possible factors that may underlie this difference include age (Berg et al., 2017), body size (Pisanski, 2014), and possibly avoiding using low frequencies not to intimidate accompanied infants (Puts et al., 2006). Our instructions to “ describe the song you chose (why you chose it, what you like about it, what the song is about, etc.)” are also different from Hilton et al.’s instructions to describe “a topic of their choice (for example…their daily routine)”, and such task differences can also affect speaking pitch (Barsties, 2013). On the other hand, this result is unlikely to be due to the exposure of Western styles to participants, since the subset of Hilton's data including only English, Mandarin, Polish, Spanish, and Kannada speakers show almost the same result as one with their full data including participants from societies less influenced by Western cultures.

After our Stage 1 Registered Report protocol received In Principle Acceptance, Albouy et al. (2023) also reanalysed Hilton et al.'s (2022) recordings using different but related methods that also emphasize pitch stability and temporal rate (“spectro-temporal modulations”). Albouy et al. transformed audio recordings to extract two-dimensional density features (spectro-temporal modulations where one axis is temporal modulations [Hz] and the other is spectral modulations [cyc/kHz]) to characterize song and speech acoustically. Their finding is similar to our results that speech has higher density in the temporal modulation range of 5-10 Hz, which matches the syllable rate and amplitude modulation rate of speech investigated cross-culturally (Ding et al., 2017; Pellegrino et al., 2011; Poeppel & Assaneo, 2020), on the low spectral modulation range (rate of change in amplitude due to vocal sound production including the initiation of utterances and the transition from consonants to vowels, which is an automated proxy of our measurement of temporal rate via manually annotated acoustic unit (e.g., syllable/mora/note) durations), and song has higher density in the spectral modulation range of 2-5 cyc/kHz on the low temporal modulation range (prominent energy in upper harmonics without fast amplitude change, potentially related to pitch stability). Their behavioral experiment further confirmed listeners rely on spectral and temporal modulation information to judge whether the uttered vocalization is song or speech, which suggests spectro-temporal modulation is an acoustic cue differentiating song and speech. Although they have not reported other features such as pitch height, the convergence of our study and their study identifying the same features implies that temporal rate and pitch stability are robust features distinguishing song and speech across cultures.

3.5.5. Evolutionary and functional mechanisms

"Discrete pitches or regular rhythmic patterns" are often considered defining features of music that distinguish it from speech (cf. Fitch, 2006; and Savage et al. 2015 block quote in the introduction), and our analyses confirmed this using a diverse cross-cultural sample. At the same time, we were surprised to find that the two features that differed most between song and speech were not pitch stability and rhythmic regularity, but rather pitch height and temporal rate (Fig. 3.5). Pitch stability was the feature differing most between *instrumental* music and spoken description, but sung pitches were substantially less stable than instrumental ones. Given that the voice is the oldest and most universal instrument, we suggest that future theories of the evolution of musicality should focus more on explaining the differences we have identified in temporal rate and pitch height. In this vein, experimental approaches such as transmission chain may be effective in capturing causal mechanisms underlying the manipulation of these parameters depending on communicative goals (e.g., Ma et al., 2019; Ozaki et al., 2023).

On the other hand, while pitch height showed larger differences between speech and song than pitch stability when comparing *within* the same individual, our exploratory analysis evaluating feature importance in song-speech classification showed that pitch stability was more useful than pitch height comparing song and speech *between* individuals. This is consistent with our intuition that song pitch can be artificially lowered in pitch and speech artificially raised in pitch without changing our categorical perception of them as song or speech. Future controlled perceptual experiments independently manipulating each feature may provide more insight on how these acoustic features are processed in our brains.

While our results do not directly provide evidence for the evolutionary mechanisms underlying differences between song and speech, we speculate that temporal rate may be a key feature underlying many observed differences. In fact, the temporal rate is the only feature showing almost no difference between singing and the instrumental (cf. Fig. S13). While slower singing reduces the amount of linguistic information that can be conveyed in the lyrics in a fixed amount of time, it gives singers more time to stabilize the pitch (which often takes some time to reach a stable plateau when singing), and the slower and more stable pitches may facilitate synchronization, harmonization, and ultimately bonding between multiple individuals (Savage et al., 2021). However, to ensure comparability between song and speech, we only asked participants to record themselves singing solo, even when songs are usually sung in groups in their culture, so future direct comparison of potential acoustic differences between solo and group vocalizations (cf. Lomax, 1968) may be needed to investigate potential relationships between our acoustic features and group synchronization/harmonization.

Furthermore, slow vocalization may also interact with high pitch vocalization since it needs deeper breaths to support sustained pitches, which may lead to an increase in subglottal pressure and accompanying higher pitch (Alipour & Scherer, 2007). The use of higher pitches in singing may also contribute to more effective communication of pitch information. Sensitivity to loudness for pure tones almost monotonically increases up to 1k Hz (Suzuki & Takeshima, 2004), but generally, the frequency range of f_0s of human voice is below 1k Hz, so it is reasonable to heighten pitches to exploit higher loudness sensitivity, which may be helpful for creating bonding through acoustic communication extensively utilizing pitch control.

The exploratory analysis of additional features can also be interpreted from the same viewpoint that extra potential differentiating features also function to enhance the saliency of pitch information: use of longer acoustic phrase, greater sound pressure, and less noisy sounds may ease the intelligibility of pitch information. On the contrary, similar timbral brightness, pitch interval size, and pitch range between song and speech may be due to motor and mechanistic constraints, like the difficulty of rapid transitioning to distanced pitch caused by the limiting control capacity of tension in the vocal folds. Since utilization of pitch can also be found in language (e.g., tonal languages; increasing the pitch of the final word in an interrogative sentence in today’s English and Japanese), inclusively probing what we can communicate with pitch in human acoustic communication may give insights into the fundamental nature of songs.

3.5.6. Inclusivity and global collaboration

Our use of a new “participants-as-coauthors” paradigm allowed us to discover new findings that would not have been possible otherwise. For example, collaboration with native/heritage speakers who recorded and annotated their own speaking/singing relying on their own Indigenous/local knowledge of their language and culture allowed us to achieve annotations faithful to their perception of vocal/instrumental sound production that we could not have achieved using automated algorithms, particularly given that there were no apparent consistent criteria about what exactly constitutes acoustic units among our participants. This resulted in our identifying surprisingly large differences for features such as temporal rate when analysed using their manual segmentations that we would have underestimated if we relied on automated segmentation (cf. combined effect size of translated Cohen’s d>1.5 in Fig. 3.5 vs. d<0.4 in Fig. S15). This highlights that equitable collaboration is not merely an issue of social justice but also of scientific quality (Nature Editors, 2022; Urassa et al., 2021).

On the other hand, this paradigm also created challenges and limitations. For example, 6 of our original 81 collaborators were unable to complete their recordings/annotations, and these were disproportionately from Indigenous and under-represented languages from our originally planned sample. Such under-represented community members tend to be disproportionately burdened with requests for representation, and some also faced additional barriers including difficulty communicating via translation, loss of internet access, and urgent crises in their communities (e.g., Nicas, 2023). Of our coauthors representing Indigenous and under-represented languages who did complete their recordings and annotations, several were not native speakers, and so their acoustic features may not necessarily reflect the way they would have been spoken by native speakers. Indeed, several of our coauthors have been involved in reviving their languages and musical cultures despite past and/or continuing threats of extinction (e.g., Ngarigu, Aynu, Hebrew; Troy & Barwick, 2020; Savage et al., 2015). By including their contributions as singers, speakers, and coauthors, we also hope to contribute to their linguistic and musical revival efforts.

Our requirement that all participant data come from coauthors, and vice versa, led to more severe sampling biases than traditional studies, as reflected in our discussion of our data showing higher, more stable-pitched singing than found in Hilton et al.'s data. Many of these limitations have been addressed through our robustness analyses and converging results from our own and Albouy et al.'s (2023) reanalyses of Hilton et al.'s independent speech/song dataset described above. However, while our exploratory analyses revealed strong sex differences in pitch height that may reflect sexual selection, most demographic factors that may affect individual differences or cultural differences in music-speech relationships (e.g., musical training, age, bilingualism) will require more comprehensive study with larger samples in the future. Because a key limitation of our participants-as-coauthors paradigm is sample size (as manual annotations are time-consuming and coauthor recruitment is more time-intensive than participant recruitment), this model may not be feasible for future larger-scale analyses. Instead, other paradigms such as targeted recruitment of individuals speaking selected languages, or mixed approaches combining manual and automated analyses may be needed.

3.6. Conclusion

Overall, our Registered Report comparing music and speech from our coauthors speaking diverse languages shows strong evidence for cross-cultural regularities in music and language amidst substantial global diversity. The features that we identified as differentiating music and speech along a "musilinguistic continuum" - particularly pitch height, temporal rate, and pitch stability - may represent promising candidates for future analyses of the (co)evolution of biological capacities for music and language (Fitch, 2006; Patel, 2008; Savage et al., 2021). Meanwhile, the features we identified as shared between speech and song - particularly timbral brightness and pitch interval size - represent promising candidates for understanding domain-general constraints on vocalization that may shape the cultural evolution of music and language (Tierney et al., 2011; Trehub, 2015; Ozaki et al., 2023; Singh & Mehr, 2023). Together, these cross-cultural similarities and differences may help shed light on the cultural and biological evolution of two systems that make us human: music and language.

Data/code availability:

Analysis code: https://github.com/comp-music-lab/song-speech-analysis

Data*:* https://osf.io/mzxc8/

Ethics:

This research has been approved by the Keio University Shonan Fujisawa Campus's Research Ethics Committee (Approval No. 449). The exploratory Maasai song/speech excerpts from non-coauthor Ole Manyas are included as part of a separate ethical approval by the Kenyan National Commision for Scientice, Technology & Innovation to Parselelo (NACOSTI/P/23/24284).

Author contributions:

-Conceived the project: Savage, Ozaki, Tierney, Pfordresher, Benetos, McBride, Proutskova, Liu, Purdy, Opondo, Jacoby, Fitch
-Funding acquisition: Savage, Ozaki, Purdy, Benetos, Jacoby, Opondo, Fitch, Thorne, Pfordresher, Liu, Rocamora
-Project management: Savage, Ozaki
-Recruitment: Savage, Ozaki, Jacoby, Opondo, Pfordresher, Fitch, Barbosa
-Translation: Barbosa, Savage, Ozaki
-Audio recordings for pilot analyses: Ozaki, Hadavi, Nweke, P. Sadaphal, McBride
-Annotations for pilot analyses: Ozaki, Hadavi, Nweke, D. Sadaphal, Savage
-Recording and text transcription/segmentation of own singing/speaking/instrumental performance: all authors
-Detailed (millisecond-level) onset annotations: Ozaki (all data), Savage (inter-rater reliability subset)
-Checking/correcting onset annotations for own singing/speaking/instrumental performance: all authors
-Conducted analyses: Ozaki
-Made Fig. 3.3 word clouds: Gomez
-Drafting initial manuscript: Ozaki, Savage
-Editing manuscript: many (but not all) authors

Inclusivity statement:

We endeavored to follow best practices in cross-cultural collaborative research (Tan & Ostashewski, 2022; Savage, Jacoby, Margulis, et al., 2023), such as involving collaborators from diverse backgrounds from the initial planning phases of a study and offering compensation via both financial (honoraria) and intellectual (coauthorship) mechanisms (see Appendix 2). Each recording set analyzed comes from a named coauthor who speaks that language as their 1st or heritage language.

Conflict of interest disclosure:

The authors of this article declare that they have no financial conflict of interest with the content of this article. Patrick Savage is a Recommender at PCI Registered Reports.

Acknowledgments:

We thank Chris Chambers, Bob Slevc, and Nai Ding for helpful reviews, and Tomoko Tanaka for serving as the Research Assistant to securely monitor and check audio recordings. We thank Joseph Bulbulia for assistance in securing funding, and thank Ozaki's PhD committee members Akira Wakita and Nao Tokui and students from the Keio University CompMusic and NeuroMusic Labs for feedback on earlier drafts of the manuscript. We thank Aritz Irurtzun, Joel Maripil, Aeles Lrawbalrate, Morzaniel Iramari Aranariutheri, Tumi Uisu Paulo Matis, and Samira Farwaneh, who initially planned to be coauthors but were unable to complete the recording and annotation processes in time.

Funding:

This work is supported by funding from the New Zealand Government, administered by the Royal Society Te Apārangi (Rutherford Discovery Fellowship 22-UOA-040 to Savage and Marsden Fast-Start Grant 22-UOA-052 to Savage, Purdy, Opondo, Jacoby, Benetos, and Fitch), and by the Japanese Government, administered by the Japan Society for the Promotion of Science (KAKENHI Grant-in-Aid #19KK0064 to Savage, Fujii, and Jacoby) and the Japan Science and Technology Agency (Grant Number JPMJSP2123 of Support for Pioneering Research Initiated by the Next Generation to Ozaki).

References:

Adams, C. R. (1976). Melodic Contour Typology. *Ethnomusicology*, 20(2), 179-215. doi:10.2307/851015

Albouy, P., Benjamin, L., Morillon, B., & Zatorre, R. J. (2020). Distinct sensitivity to spectrotemporal modulation supports brain asymmetry for speech and melody. *Science*, *367*(6481), 1043–1047. https://doi.org/10.1126/science.aaz3468

Albouy, P., Mehr, S. A., Hoyer, R. S., Ginzburg, J., & Zatorre, R. J. (2023). Spectro-temporal acoustical markers differentiate speech from song across cultures . *bioRxiv* preprint:. https://doi.org/10.1101/2023.01.29.526133

Alipour, F., & Scherer, R. C. (2007). On pressure-frequency relations in the excised larynx. *The Journal of the Acoustical Society of America*, *122*(4), 2296–2305. https://doi.org/10.1121/1.2772230

Anikin, A. (2020). The link between auditory salience and emotion intensity. *Cognition and Emotion*, *34*(6), 1246–1259. https://doi.org/10.1080/02699931.2020.1736992

Anvari, F., & Lakens, D. (2021). Using anchor-based methods to determine the smallest effect size of interest. *Journal of Experimental Social Psychology*, *96*, 104159. https://doi.org/10.1016/j.jesp.2021.104159

Barbosa, P. A., Arantes, P., Meireles, A. R., & Vieira, J. M. (2005). Abstractness in speech-metronome synchronisation: P-centres as cyclic attractors. *Interspeech 2005*, 1441–1444. https://doi.org/10.21437/Interspeech.2005-512

Barnes, J. J., Davis, P., Oates, J., & Chapman, J. (2004). The relationship between professional operatic soprano voice and high range spectral energy. *The Journal of the Acoustical Society of America*, *116*(1), 530–538. https://doi.org/10.1121/1.1710505

Barsties, B. (2013). Einfluss verschiedener Methoden zur Bestimmung der mittleren Sprechstimmlage. *HNO*, *61*(7), 609–616. https://doi.org/10.1007/s00106-012-2665-0

Bârzan, H., Moca, V. V., Ichim, A.-M., & Muresan, R. C. (2021). Fractional Superlets. *2020 28th European Signal Processing Conference (EUSIPCO)*, 2220–2224. https://doi.org/10.23919/Eusipco47968.2020.9287873

Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, *57*(1), 289–300.

Berg, M., Fuchs, M., Wirkner, K., Loeffler, M., Engel, C., & Berger, T. (2017). The Speaking Voice in the General Population: Normative Data and Associations to Sociodemographic and Lifestyle Factors. *Journal of Voice*, *31*(2), 257.e13-257.e24. https://doi.org/10.1016/j.jvoice.2016.06.001

Bickel, B. (2011). Absolute and statistical universals. In *The Cambridge Encyclopedia of the Language Sciences*, P. C. Hogan, ed. (Cambridge University Press), pp. 77–79.

Blacking, J. (1973). *How musical is man?* University of Washington Press.

Blasi, D. E., Henrich, J., Adamou, E., Kemmerer, D., & Majid, A. (2022). Over-reliance on English hinders cognitive science. *Trends in Cognitive Sciences*, https://doi.org/10.1016/j.tics.2022.09.015

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Bozdogan, H. (1987). Model selection and Akaike's Information Criterion (AIC): The general theory and its analytical extensions. *Psychometrika*, *52*(3), 345–370. https://doi.org/10.1007/BF02294361

Brockwell, S. E., & Gordon, I. R. (2001). A comparison of statistical methods for meta-analysis. *Statistics in Medicine*, *20*(6), 825–840. https://doi.org/10.1002/sim.650

Brown, D. E. (1991). *Human Universals*. New York: McGraw-Hill.

Brown, S. (2000). The Musilanguage Model of Music Evolution. In S. Brown, B. Merker, & C. Wallin (Eds.), *The Origins of Music* (pp. 271–300). The MIT Press.

Brown, S., & Jordania, J. (2013). Universals in the world's musics. *Psychology of Music*, *41*(2), 229–248. https://doi.org/10.1177/0305735611425896

Brown, S., Savage, P. E., Ko, A. M.-S., Stoneking, M., Ko, Y.-C., Loo, J.-H., & Trejaut, J. A. (2014). Correlations in the population structure of music, genes and language. *Proceedings of the Royal Society B: Biological Sciences*, *281*(1774), 20132072. https://doi.org/10.1098/rspb.2013.2072

Brunner E., Bathke A. C., & Konietschke F. (2018). *Rank and pseudo-rank procedures for independent observations in factorial designs: Using R and SAS*. Springer. https://ci.nii.ac.jp/ncid/BB28708839

Bryant, G. A. (2021). The Evolution of Human Vocal Emotion. *Emotion Review*, *13*(1), 25–33. https://doi.org/10.1177/1754073920930791

Brysbaert, M. (2019). How many participants do we have to include in properly powered experiments? A tutorial of power analysis with reference tables. *Journal of Cognition*, *2*(1), 16. https://doi.org/10.5334/joc.72

Cannam, C., Landone, C., & Sandler, M. (2010). Sonic visualiser: An open source application for viewing, analysing, and annotating music audio files. *Proceedings of the 18th ACM International Conference on Multimedia*, 1467–1468. https://doi.org/10.1145/1873951.1874248

Chacón, J. E. (2020). The Modal Age of Statistics. *International Statistical Review*, *88*(1), 122–141. https://doi.org/10.1111/insr.12340

Chang, A., Teng, X., Assaneo, F., & Poeppel, D. (2022). *Amplitude modulation perceptually distinguishes music and speech*. *PsyArXiv* preprint: https://doi.org/10.31234/osf.io/juzrh

Chazal, F., Fasy, B., Lecci, F., Bertr, Michel, Aless, Rinaldo, R., & Wasserman, L. (2018). Robust Topological Inference: Distance To a Measure and Kernel Distance. *Journal of Machine Learning Research*, *18*(159), 1–40.

Chaudhuri, P., & Marron, J. S. (1999). SiZer for Exploration of Structures in Curves. *Journal of the American Statistical Association*, *94*(447), 807–823. https://doi.org/10.1080/01621459.1999.10474186

Chen, S., Han, C., Wang, S., Liu, X., Wang, B., Wei, R., & Lei, X. (2022). Hearing the physical condition: The relationship between sexually dimorphic vocal traits and underlying physiology. *Frontiers in Psychology*, *13*. https://www.frontiersin.org/articles/10.3389/fpsyg.2022.983688

Chen, Y.-C., Genovese, C. R., Ho, S., & Wasserman, L. (2015). Optimal Ridge Detection using Coverage Risk. *Advances in Neural Information Processing Systems*, *28*. https://papers.nips.cc/paper/2015/hash/0aa1883c6411f7873cb83dacb17b0afc-Abstract.html

Chen, Y.-C., Genovese, C. R., & Wasserman, L. (2016). A comprehensive approach to mode clustering. *Electronic Journal of Statistics*, *10*(1), 210–241. https://doi.org/10.1214/15-EJS1102

Cheney, D. L., & Seyfarth, R. M. (2018). Flexible usage and social function in primate vocalizations. *Proceedings of the National Academy of Sciences*, *115*(9), 1974–1979. https://doi.org/10.1073/pnas.1717572115

Chow, I., Belyk, M., Tran, V., & Brown, S. (2015). Syllable synchronization and the P-center in Cantonese. *Journal of Phonetics*, *49*, 55–66. https://doi.org/10.1016/j.wocn.2014.10.006

Comaniciu, D., & Meer, P. (2002). Mean shift: A robust approach toward feature space analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *24*(5), 603–619. https://doi.org/10.1109/34.1000236

Cooper, A. M., Whalen, D. H., & Fowler, C. A. (1986). P-centers are unaffected by phonetic categorization. *Perception & Psychophysics*, *39*(3), 187–196. https://doi.org/10.3758/BF03212490

Cox, C., Bergmann, C., Fowler, E., Keren-Portnoy, T., Roepstorff, A., Bryant, G., & Fusaroli, R. (2022). A systematic review and Bayesian meta-analysis of the acoustic features of infant-directed speech. *Nature Human Behaviour*, 1–20. https://doi.org/10.1038/s41562-022-01452-1

Cychosz, M., Cristia, A., Bergelson, E., Casillas, M., Baudet, G., Warlaumont, A. S., Scaff, C., Yankowitz, L., & Seidl, A. (2021). Vocal development in a large-scale crosslinguistic corpus. *Developmental Science*, *24*(5), e13090. https://doi.org/10.1111/desc.13090

Danielsen, A., Nymoen, K., Anderson, E., Câmara, G. S., Langerød, M. T., Thompson, M. R., & London, J. (2019). Where is the beat in that note? Effects of attack, duration, and frequency on the perceived timing of musical and quasi-musical sounds. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(3), 402–418. https://doi.org/10.1037/xhp0000611

Darwin, C. (1871). *The descent of man*. Watts & Co.

Dell, G. S., Schwartz, M. F., Martin, N., Saffran, E. M., & Gagnon, D. A. (2000). The role of computational models in neuropsychological investigations of language: Reply to Ruml and Caramazza (2000). *Psychological Review*, *107*, 635–645. https://doi.org/10.1037/0033-295X.107.3.635

DerSimonian, R., & Laird, N. (1986). Meta-analysis in clinical trials. *Controlled Clinical Trials*, *7*(3), 177–188. https://doi.org/10.1016/0197-2456(86)90046-2

Ding, N., Patel, A. D., Chen, L., Butler, H., Luo, C., & Poeppel, D. (2017). Temporal modulations in speech and music. *Neuroscience & Biobehavioral Reviews*, *81*, 181–187. https://doi.org/10.1016/j.neubiorev.2017.02.011

Djurović, I., & Stanković, Lj. (2004). An algorithm for the Wigner distribution based instantaneous frequency estimation in a high noise environment. *Signal Processing*, *84*(3), 631–643. https://doi.org/10.1016/j.sigpro.2003.12.006

Doelling, K. B., Assaneo, M. F., Bevilacqua, D., Pesaran, B., & Poeppel, D. (2019). An oscillator model better predicts cortical entrainment to music. *Proceedings of the National Academy of Sciences*, *116*(20), 10113–10121. https://doi.org/10.1073/pnas.1816414116

Dryer, Matthew S. & Haspelmath, Martin (eds.) 2013. *The World Atlas of Language Structures Online*. Leipzig: Max Planck Institute for Evolutionary Anthropology. (Available online at http://wals.info, Accessed on 2022-10-03.)

Dunn, M., Greenhill, S. J., Levinson, S. C., & Gray, R. D. (2011). Evolved structure of language shows lineage-specific trends in word-order universals. *Nature*, *473*(7345), 79–82. https://doi.org/10.1038/nature09923

Durojaye, C., Fink, L., Roeske, T., Wald-Fuhrmann, M., & Larrouy-Maestri, P. (2021). Perception of Nigerian Dùndún Talking Drum Performances as Speech-Like vs. Music-Like: The Role of Familiarity and Acoustic Cues. *Frontiers in Psychology*, *12*. https://www.frontiersin.org/articles/10.3389/fpsyg.2021.652673

Evans, N., and Levinson, S.C. (2009). The myth of language universals: Language diversity and its importance for cognitive science. *Behav. Brain Sci.* 32, 429–492.

Fasy, B. T., Lecci, F., Rinaldo, A., Wasserman, L., Balakrishnan, S., & Singh, A. (2014). Confidence sets for persistence diagrams. *The Annals of Statistics*, *42*(6), 2301–2339. https://doi.org/10.1214/14-AOS1252

Feinberg, D. R., Jones, B. C., & Armstrong, M. M. (2018). Sensory Exploitation, Sexual Dimorphism, and Human Voice Pitch. *Trends in Ecology & Evolution*, *33*(12), 901–903. https://doi.org/10.1016/j.tree.2018.09.007

Fitch, W. T. (2006). The biology and evolution of music: A comparative perspective. *Cognition*, *100*(1), 173–215. https://doi.org/10.1016/j.cognition.2005.11.009

Fraser, D. (1989). Interpolation by the FFT revisited-an experimental investigation. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, *37*(5), 665–675. https://doi.org/10.1109/29.17559

Freeberg, T. M., Dunbar, R. I. M., & Ord, T. J. (2012). Social complexity as a proximate and ultimate factor in communicative complexity. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *367*(1597), 1785–1801. https://doi.org/10.1098/rstb.2011.0213

Genovese, C. R., Perone-Pacifico, M., Verdinelli, I., & Wasserman, L. (2014). Nonparametric ridge estimation. *The Annals of Statistics*, *42*(4), 1511–1545. https://doi.org/10.1214/14-AOS1218

Genovese, C. R., Perone-Pacifico, M., Verdinelli, I., & Wasserman, L. (2016). Non-parametric inference for density modes. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, *78*(1), 99–126.

Grabe, E., & Low, E. L. (2002). Durational variability in speech and the Rhythm Class Hypothesis. In C. Gussenhoven & N. Warner (Eds.), *Laboratory Phonology 7* (pp. 515–546). De Gruyter Mouton. https://doi.org/10.1515/9783110197105.2.515

Haiduk, F., Quigley, C., & Fitch, W. T. (2020). Song Is More Memorable Than Speech Prosody: Discrete Pitches Aid Auditory Working Memory. *Frontiers in Psychology*, *11*. https://www.frontiersin.org/article/10.3389/fpsyg.2020.586723

Haiduk, F., & Fitch, W. T. (2022). Understanding Design Features of Music and Language: The Choric/Dialogic Distinction. *Frontiers in Psychology*, *13*. https://www.frontiersin.org/article/10.3389/fpsyg.2022.786899

Hall, P., Sheather, S. J., Jones, M. C., & Marron, J. S. (1991). On Optimal Data-Based Bandwidth Selection in Kernel Density Estimation. *Biometrika*, *78*(2), 263–269. https://doi.org/10.2307/2337251

Hammarström, H., Forkel, R., Haspelmath, M., & Bank, S. (2022). Glottolog 4.7. Leipzig: Max Planck Institute for Evolutionary Anthropology. https://doi.org/10.5281/zenodo.7398962 (Available online at http://glottolog.org, Accessed on 2023-05-14.)

Han, S. er, Sundararajan, J., Bowling, D. L., Lake, J., & Purves, D. (2011). Co-Variation of Tonality in the Music and Speech of Different Cultures. *PLOS ONE*, *6*(5), e20160. https://doi.org/10.1371/journal.pone.0020160

Hansen, J. H. L., Bokshi, M., & Khorram, S. (2020). Speech variability: A cross-language study on acoustic variations of speaking versus untrained singing. *The Journal of the Acoustical Society of America*, *148*(2), 829. https://doi.org/10.1121/10.0001526

Hilton, C. B., Moser, C. J., Bertolo, M., Lee-Rubin, H., Amir, D., Bainbridge, C. M., Simson, J., Knox, D., Glowacki, L., Alemu, E., Galbarczyk, A., Jasienska, G., Ross, C. T., Neff, M. B., Martin, A., Cirelli, L. K., Trehub, S. E., Song, J., Kim, M., … Mehr, S. A. (2022). Acoustic regularities in infant-directed speech and song across cultures. *Nature Human Behaviour*, 1–12. https://doi.org/10.1038/s41562-022-01410-x

Hoeschele, M., & Fitch, W. T. (2022). Cultural evolution: Conserved patterns of melodic evolution across musical cultures. *Current Biology*, *32*(6), R265–R267. https://doi.org/10.1016/j.cub.2022.01.080

Horn, M., & Dunnett, C. W. (2004). Power and sample size comparisons of stepwise FWE and FDR controlling test procedures in the normal many-one case. *Recent Developments in Multiple Comparison Procedures*, *47*, 48–65. https://doi.org/10.1214/lnms/1196285625

Howell, P. (1988). Prediction of P-center location from the distribution of energy in the amplitude envelope: I. *Perception & Psychophysics*, *43*(1), 90–93. https://doi.org/10.3758/BF03208978

Jackson, D., & Turner, R. (2017). Power analysis for random-effects meta-analysis. *Research Synthesis Methods*, *8*(3), 290–302. https://doi.org/10.1002/jrsm.1240

Jacoby, N., Margulis, E.H., Clayton, M., Hannon, E., Honing, H., Iversen, J., Klein, T.R., Mehr, S.A., Pearson, L., Peretz, I., Savage, P. E., et al. (2020). Cross-cultural work in music cognition: Methodologies, pitfalls, and practices. *Music Percept.* 37, 185–195.

Johnston, J. D. (1988). Transform coding of audio signals using perceptual noise criteria. *IEEE Journal on Selected Areas in Communications*, *6*(2), 314–323. https://doi.org/10.1109/49.608

de Jong, N. H., & Wempe, T. (2009). Praat script to detect syllable nuclei and measure speech rate automatically. *Behavior Research Methods*, *41*(2), 385–390. https://doi.org/10.3758/BRM.41.2.385

Jung, S.-H. (2005). Sample size for FDR-control in microarray data analysis. *Bioinformatics*, *21*(14), 3097–3104. https://doi.org/10.1093/bioinformatics/bti456

Ladd, D. R. (1984). Declination: A review and some hypotheses. *Phonology*, 1, 53-74.

Lakens, D. (2017). Equivalence Tests: A Practical Primer for t Tests, Correlations, and Meta-Analyses. *Social Psychological and Personality Science*, *8*(4), 355–362. https://doi.org/10.1177/1948550617697177

Lartillot, O., Eerola, T., Toiviainen, P., & Fornari, J. (2008). Multi-feature modeling of pulse clarity: Design, validation and optimization. *Proc. of the 9th Int. Society for Music Information Retrieval Conf.*, 521–526.

Lartillot, O., Toiviainen, P., & Eerola, T. (2008). A Matlab Toolbox for Music Information Retrieval. In C. Preisach, H. Burkhardt, L. Schmidt-Thieme, & R. Decker (Eds.), *Data Analysis, Machine Learning and Applications* (pp. 261–268). Springer. https://doi.org/10.1007/978-3-540-78246-9_31

Leongómez, J. D., Havlíček, J., & Roberts, S. C. (2022). Musicality in human vocal communication: An evolutionary perspective. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *377*(1841), 20200391. https://doi.org/10.1098/rstb.2020.0391

Lindblom, B., & Sundberg, J. (2007). The Human Voice in Speech and Singing. In T. D. Rossing (Ed.), *Springer Handbook of Acoustics* (pp. 669–712). Springer. https://doi.org/10.1007/978-0-387-30425-0_16

Ling, L. E., Grabe, E., & Nolan, F. (2000). Quantitative Characterizations of Speech Rhythm: Syllable-Timing in Singapore English. *Language and Speech*, *43*(4), 377–401. https://doi.org/10.1177/00238309000430040301

List, G. (1971). On the Non-Universality of Musical Perspectives. *Ethnomusicology*, *15*(3), 399–402.

Liu, S., Tian, L., Lee, S., & Xie, M. (2018). Exact inference on meta-analysis with generalized fixed-effects and random-effects models. *Biostatistics & Epidemiology*, *2*(1), 1–22. https://doi.org/10.1080/24709360.2017.1400714

Lomax, A., & Grauer, V. (1968). The Cantometric coding book. In A. Lomax (Ed.), *Folk song style and culture* (pp. 34–74). American Association for the Advancement of Science.

Ma, W., Fiveash, A., & Thompson, W. F. (2019). Spontaneous emergence of language-like and music-like vocalizations from an artificial protolanguage. *Semiotica*, *2019*(229), 1–23. https://doi.org/10.1515/sem-2018-0139

Matsumae, H., Ranacher, P., Savage, P. E., Blasi, D. E., Currie, T. E., Koganebuchi, K., Nishida, N., Sato, T., Tanabe, H., Tajima, A., Brown, S., Stoneking, M., Shimizu, K. K., Oota, H., & Bickel, B. (2021). Exploring correlations in genetic and cultural variation across language families in northeast Asia. *Science Advances*. https://doi.org/10.1126/sciadv.abd9223

Mauch, M., & Dixon, S. (2014). PYIN: A fundamental frequency estimator using probabilistic threshold distributions. *2014 IEEE International Conference on*

Acoustics, Speech and Signal Processing (ICASSP), 659–663. https://doi.org/10.1109/ICASSP.2014.6853678

Mehr, S. A., Singh, M., Knox, D., Ketter, D. M., Pickens-Jones, D., Atwood, S., Lucas, C., Jacoby, N., Egner, A. A., Hopkins, E. J., Howard, R. M., Hartshorne, J. K., Jennings, M. V., Simson, J., Bainbridge, C. M., Pinker, S., O'Donnell, T. J., Krasnow, M. M., & Glowacki, L. (2019). Universality and diversity in human song. *Science*, *366*(6468), eaax0868. https://doi.org/10.1126/science.aax0868

Mehr, S. A., Krasnow, M. M., Bryant, G. A., & Hagen, E. H. (2021). Origins of music in credible signaling. *Behavioral and Brain Sciences*, *44*. https://doi.org/10.1017/S0140525X20000345

Merrill, J., & Larrouy-Maestri, P. (2017). Vocal Features of Song and Speech: Insights from Schoenberg's Pierrot Lunaire. *Frontiers in Psychology*, *8*, 1108. https://doi.org/10.3389/fpsyg.2017.01108

Mertens, P. (2022). The Prosogram model for pitch stylization and its applications in intonation transcription. In J. Barnes & S. Shattuck-Hufnagel (Eds.), *Prosodic Theory and Practice* (pp. 259–286). MIT Press. https://mitpress.mit.edu/9780262543170/prosodic-theory-and-practice/

Moca, V. V., Bârzan, H., Nagy-Dăbâcan, A., & Mureșan, R. C. (2021). Time-frequency super-resolution with superlets. *Nature Communications*, *12*(1), 337. https://doi.org/10.1038/s41467-020-20539-9

Morrill, T. H., McAuley, J. D., Dilley, L. C., & Hambrick, D. Z. (2015). Individual differences in the perception of melodic contours and pitch-accent timing in speech: Support for domain-generality of pitch processing. *Journal of Experimental Psychology: General*, *144*, 730–736. https://doi.org/10.1037/xge0000081

Morton, J., Marcus, S., & Frankish, C. (1976). Perceptual centers (P-centers). *Psychological Review*, *83*(5), 405–408. https://doi.org/10.1037/0033-295X.83.5.405

Müller, M., Rosenzweig, S., Driedger, J., & Scherbaum, F. (2017, June 13). *Interactive Fundamental Frequency Estimation with Applications to Ethnomusicological Research*. Audio Engineering Society Conference: 2017 AES International Conference on Semantic Audio. https://www.aes.org/e-lib/browse.cfm?elib=18777

Natke, U., Donath, T. M., & Kalveram, K. Th. (2003). Control of voice fundamental frequency in speaking versus singing. *Journal of the Acoustical Society of America*, *113*(3), 1587–1593. https://doi.org/10.1121/1.1543928

Nature Editors. (2022). Nature addresses helicopter research and ethics dumping. *Nature*, *606*(7912), 7–7. https://doi.org/10.1038/d41586-022-01423-6

Nicas, J. (2023, March 25). The Amazon's Largest Isolated Tribe Is Dying. *The New York Times*. https://www.nytimes.com/2023/03/25/world/americas/brazil-amazon-indigenous-tribe.html

Nikolsky, A., Alekseyev, E., Alekseev, I., & Dyakonova, V. (2020). The Overlooked Tradition of "Personal Music" and Its Place in the Evolution of Music. *Frontiers in Psychology*, *10*. https://www.frontiersin.org/article/10.3389/fpsyg.2019.03051

Nordhoff, S., & Hammarstrom, H. (2011). Glottolog/Langdoc: Defining dialects, languages, and language families as collections of resources. *Proceedings of ISWC 2011*, 1–6.

Novitski, N., Tervaniemi, M., Huotilainen, M., & Näätänen, R. (2004). Frequency discrimination at different frequency levels as indexed by electrophysiological and behavioral measures. *Cognitive Brain Research*, *20*(1), 26–36. https://doi.org/10.1016/j.cogbrainres.2003.12.011

Ozaki, Y., Sato, S., McBride, J.M., Pfordresher, P.Q., Tierney, A.T., Six, J., Fujii, S., and Savage, P.E. (2022). Automatic acoustic analyses quantify pitch discreteness within and between human music, speech, and bird song. *Proc. 10th Int. Folk Music Anal. Work.*

Ozaki, Y., Kuroyanagi, J., Chiba, G., McBride, J., Proutskova, P., Tierney, A. T., Pfordresher, P. Q., Benetos, E., Liu, F., & Savage, P. E. (2022). Similarities and differences in a cross-linguistic sample of song and speech recordings. *Proceedings of the 2022 Joint Conference on Language Evolution*, 569–572.

Ozaki, Y., de Heer Kloots, M., Ravignani, A., & Savage, P. E. (2023) Cultural evolution of music and language. In D. Sammler (Ed.), *Oxford Handbook of Language and Music*. Oxford University Press. Preprint: https://doi.org/10.31234/osf.io/s7apx

Passmore, S., Wood, A. L. C., Barbieri, C., Shilton, D., Daikoku, H., Atkinson, Q. D., & Savage, P. E. (Under review). Independent histories underlie global musical, linguistic, and genetic diversity.

Patel, A. D. (2008). *Music, language and the brain*. Oxford University Press.

Patel, A. D. (2011). Language, music, and the brain: A resource-sharing framework. In P. Rebuschat, M. Rohmeier, J. A. Hawkins, & I. Cross (Eds.), *Language and Music as Cognitive Systems* (p. 204-223). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199553426.003.0022

Patel, A. D. (2018). Music as a transformative technology of the mind: An update. In H. Honing (Ed.), *The origins of musicality* (pp. 113–126). MIT Press.

Patel, A. D., & Daniele, J. R. (2003). An empirical comparison of rhythm in language and music. *Cognition*, 87(1), 35–45.

Patel, A. D., Iversen, J. R., & Rosenberg, J. C. (2006). Comparing the rhythm and melody of speech and music: The case of British English and French. *The Journal of the Acoustical Society of America*, *119*(5), 3034–3047. https://doi.org/10.1121/1.2179657

Patel, A. D., & Rueden, C. von. (2021). Where they sing solo: Accounting for cross-cultural variation in collective music-making in theories of music evolution. *Behavioral and Brain Sciences*, *44*, e85. https://doi.org/10.1017/S0140525X20001089

Peeters, G. (2004). *A large set of audio features for sound description (similarity and classification) in the Cuidado Project* [Technical Report]. Institut de Recherche et Coordination Acoustique/Musique (IRCAM).

Pellegrino, F., Coupé, C., & Marsico, E. (2011). A Cross-Language Perspective on Speech Information Rate. *Language*, *87*(3), 539–558.

Pereira, J. P. B., Stroes, E. S. G., Zwinderman, A. H., & Levin, E. (2022). Covered Information Disentanglement: Model Transparency via Unbiased Permutation Importance. *Proceedings of the AAAI Conference on Artificial Intelligence*, *36*(7), Article 7. https://doi.org/10.1609/aaai.v36i7.20769

Peretz, I. (2009). Music, Language and Modularity Framed in Action. *Psychologica Belgica*, *49*(2–3), Article 2–3. https://doi.org/10.5334/pb-49-2-3-157

Pemutatoin Importance (n.d.). ELI5, Retrieved May 10, 2023, from https://eli5.readthedocs.io/en/latest/blackbox/permutation_importance.html

Pfordresher, P. Q., Brown, S., Meier, K. M., Belyk, M., & Liotti, M. (2010). Imprecise singing is widespread. *The Journal of the Acoustical Society of America*, *128*(4), 2182–2190. https://doi.org/10.1121/1.3478782

Pisanski, K., Fraccaro, P. J., Tigue, C. C., O'Connor, J. J. M., Röder, S., Andrews, P. W., Fink, B., DeBruine, L. M., Jones, B. C., & Feinberg, D. R. (2014). Vocal indicators of body size in men and women: A meta-analysis. *Animal Behaviour*, *95*, 89–99. https://doi.org/10.1016/j.anbehav.2014.06.011

Poeppel, D., & Assaneo, M. F. (2020). Speech rhythms and their neural foundations. *Nature Reviews Neuroscience*, *21*(6), 322–334. https://doi.org/10.1038/s41583-020-0304-4

Pompino-Marschall, B. (1989). On the psychoacoustic nature of the P-center phenomenon. *Journal of Phonetics*, *17*(3), 175–192. https://doi.org/10.1016/S0095-4470(19)30428-0

Pounds, S., & Cheng, C. (2005). Sample size determination for the false discovery rate. *Bioinformatics*, *21*(23), 4263–4271. https://doi.org/10.1093/bioinformatics/bti699

Puts, D. A., Gaulin, S. J. C., & Verdolini, K. (2006). Dominance and the evolution of sexual dimorphism in human voice pitch. *Evolution and Human Behavior*, *27*(4), 283–296. https://doi.org/10.1016/j.evolhumbehav.2005.11.003

Puts, D. A., Hill, A. K., Bailey, D. H., Walker, R. S., Rendall, D., Wheatley, J. R., Welling, L. L. M., Dawood, K., Cárdenas, R., Burriss, R. P., Jablonski, N. G., Shriver, M. D., Weiss, D., Lameira, A. R., Apicella, C. L., Owren, M. J., Barelli, C., Glenn, M. E., & Ramos-Fernandez, G. (2016). Sexual selection on male vocal fundamental frequency in humans and other anthropoids. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1829), 20152830. https://doi.org/10.1098/rspb.2015.2830

Raposo de Medeiros, B., Cabral, J. P., Meireles, A. R., & Baceti, A. A. (2021). A comparative study of fundamental frequency stability between speech and singing. *Speech Communication*, *128*, 15–23. https://doi.org/10.1016/j.specom.2021.02.003

Robledo, J. P., Hurtado, E., Prado, F., Román, D., & Cornejo, C. (2016). Music intervals in speech: Psychological disposition modulates ratio precision among interlocutors' nonlocal f0 production in real-time dyadic conversation. *Psychology of Music*, *44*(6), 1404–1418. https://doi.org/10.1177/0305735616634452

Roeske, T. C., Tchernichovski, O., Poeppel, D., & Jacoby, N. (2020). Categorical Rhythms Are Shared between Songbirds and Humans. *Current Biology*, 30(18), 3544-3555.e6. https://doi.org/10.1016/j.cub.2020.06.072

Rogalsky, C., Rong, F., Saberi, K., & Hickok, G. (2011). Functional Anatomy of Language and Music Perception: Temporal and Structural Factors Investigated Using Functional Magnetic Resonance Imaging. *Journal of Neuroscience*, *31*(10), 3843–3852. https://doi.org/10.1523/JNEUROSCI.4515-10.2011

Romano, J. P. (2005). Optimal testing of equivalence hypotheses. *The Annals of Statistics*, *33*(3), 1036–1047. https://doi.org/10.1214/009053605000000048

Rosenzweig, S., Scherbaum, F., Shugliashvili, D., Arifi-Müller, V., & Müller, M. (2020). Erkomaishvili Dataset: A Curated Corpus of Traditional Georgian Vocal Music for Computational Musicology. *Transactions of the International Society for Music Information Retrieval*, *3*(1), 31–41. https://doi.org/10.5334/tismir.44

Ross, D., Choi, J., & Purves, D. (2007). Musical intervals in speech. *Proceedings of the National Academy of Sciences*, *104*(23), 9852–9857. https://doi.org/10.1073/pnas.0703140104

Ruscio, J. (2008). A probability-based measure of effect size: Robustness to base rates and other factors. *Psychological Methods*, *13*(1), 19–30. https://doi.org/10.1037/1082-989X.13.1.19

Savage, P. E. (2019). Universals. In J. L. Sturman (Ed.), *The SAGE International Encyclopedia of Music and Culture* (p. 2282–2285). Thousand Oaks: SAGE Publications. http://doi.org/10.4135/9781483317731.n759

Savage, P. E., Brown, S., Sakai, E., & Currie, T. E. (2015). Statistical universals reveal the structures and functions of human music. *Proceedings of the National Academy of Sciences*, *112*(29), 8987–8992. https://doi.org/10.1073/pnas.1414495112

Savage, P. E., Loui, P., Tarr, B., Schachner, A., Glowacki, L., Mithen, S., & Fitch, W. T. (2021). Music as a coevolved system for social bonding. *Behavioral and Brain Sciences*, *44*. https://doi.org/10.1017/S0140525X20000333

Savage, P. E., Loui, P., Tarr, B., Schachner, A., Glowacki, L., Mithen, S., & Fitch, W. T. (2021b). Authors' response: Toward inclusive theories of the evolution of musicality. *Behavioral and Brain Sciences*, 44(e121), 132–140. https://doi.org/10.1017/S0140525X21000042

Savage, P.E., Jacoby, N., Margulis, E.H., Daikoku, H., Anglada-Tort, M., Castelo-Branco, S.E.-S., Nweke, F.E., Fujii, S., Hegde, S., Chuan-Peng, H., Opondo, P., et al. (2023). Building sustainable global collaborative networks: Recommendations from music studies and the social sciences. In E. H. Margulis, D. Loughridge, and P. Loui (Eds.), *The science-music borderlands: Reckoning with the past, imagining the future* (347-365). MIT Press. https://doi.org/10.7551/mitpress/14186.003.0032

Savage, P. E., Matsumae, H., Oota, H., Stoneking, M., Currie, T. E., Tajima, A., Gillan, M., & Brown, S. (2015). How "circumpolar" is Ainu music? Musical and genetic perspectives on the history of the Japanese archipelago. Ethnomusicology Forum, 24(3), 443–467. https://doi.org/10.1080/17411912.2015.1084236

Schafer, R. W., & Rabiner, L. R. (1973). A digital signal processing approach to interpolation. *Proceedings of the IEEE*, *61*(6), 692–702. https://doi.org/10.1109/PROC.1973.9150

Schamberg, I., Wittig, R. M., & Crockford, C. (2018). Call type signals caller goal: A new take on ultimate and proximate influences in vocal production. *Biological Reviews*, *93*(4), 2071–2082. https://doi.org/10.1111/brv.12437

Schwartz, D. A., Howe, C. Q., & Purves, D. (2003). The Statistical Structure of Human Speech Sounds Predicts Musical Universals. *Journal of Neuroscience*, *23*(18), 7160–7168. https://doi.org/10.1523/JNEUROSCI.23-18-07160.2003

Scott, S. K. (1998). The point of P-centres. *Psychological Research*, *61*(1), 4–11. https://doi.org/10.1007/PL00008162

Sera, F., Armstrong, B., Blangiardo, M., & Gasparrini, A. (2019). An extended mixed-effects framework for meta-analysis. *Statistics in Medicine*, *38*(29), 5429–5444. https://doi.org/10.1002/sim.8362

Shao, X., & Ma, C. (2003). A general approach to derivative calculation using wavelet transform. *Chemometrics and Intelligent Laboratory Systems*, *69*(1), 157–165. https://doi.org/10.1016/j.chemolab.2003.08.001

Sharma, B., Gao, X., Vijayan, K., Tian, X., & Li, H. (2021). NHSS: A speech and singing parallel database. *Speech Communication*, *133*, 9–22. https://doi.org/10.1016/j.specom.2021.07.002

Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*. Chapman and Hall. https://doi.org/10.1201/9781315140919

Singh, M., & Mehr, S. A. (2023). Universality, domain-specificity and development of psychological responses to music. *Nature Reviews Psychology*, 1–14. https://doi.org/10.1038/s44159-023-00182-z

Slifka, J. (2006). Respiratory system pressures at the start of an utterance. In P. Divenyi, S. Greenberg, & G. Meyer (Eds.), *Dynamics of speech production and perception* (pp. 45-57). Amsterdam: IOS Press.

Sommerfeld, M., Heo, G., Kim, P., Rush, S. T., & Marron, J. S. (2017). Bump hunting by topological data analysis. *Stat*, *6*(1), 462–471. https://doi.org/10.1002/sta4.167

Stegemöller, E. L., Skoe, E., Nicol, T., Warrier, C. M., & Kraus, N. (2008). Music Training and Vocal Production of Speech and Song. *Music Perception*, *25*(5), 419–428. https://doi.org/10.1525/mp.2008.25.5.419

Stone, R. E. (Ed), Cleveland, T. F., & Sundberg, J. (1999). Formant frequencies in country singers' speech and singing. *Journal of Voice*, *13*(2), 161–167. https://doi.org/10.1016/S0892-1997(99)80020-4

Sundberg, J. (2001). Level and Center Frequency of the Singer's Formant. *Journal of Voice*, *15*(2), 176–186. https://doi.org/10.1016/S0892-1997(01)00019-4

Suzuki, Y., & Takeshima, H. (2004). Equal-loudness-level contours for pure tones. *The Journal of the Acoustical Society of America*, *116*(2), 918–933. https://doi.org/10.1121/1.1763601

Tan, S. B., & Ostashewski, M. (Eds.). (2022). *DIALOGUES: Towards decolonizing music and dance studies*. International Council for Traditional Music. https://ictmdialogues.org/

Tan, Z.-H., Sarkar, A. kr., & Dehak, N. (2020). rVAD: An unsupervised segment-based robust voice activity detection method. *Computer Speech & Language*, *59*, 1–21. https://doi.org/10.1016/j.csl.2019.06.005

Thompson, B. (2014). Discrimination between singing and speech in real-world audio. *2014 IEEE Spoken Language Technology Workshop (SLT)*, 407–412. https://doi.org/10.1109/SLT.2014.7078609

Tierney, A. T., Russo, F. A., & Patel, A. D. (2011). The motor origins of human and avian song structure. *Proceedings of the National Academy of Sciences*, *108*(37), 15510–15515. https://doi.org/10.1073/pnas.1103882108

Trehub, S. E., Unyk, A. M., Kamenetsky, S. B., Hill, D. S., Trainor, L. J., Henderson, J. L., & Saraza, M. (1997). Mothers' and fathers' singing to infants. *Developmental Psychology*, *33*(3), 500–507. https://doi.org/10.1037/0012-1649.33.3.500

Troy, J., & Barwick, L. (2020). Claiming the 'Song of the Women of the Menero Tribe.' *Musicology Australia*, 42(2), 85–107. https://doi.org/10.1080/08145857.2020.1945254

Tsur, R., & Gafni, C. (2022). *Sound–Emotion Interaction in Poetry: Rhythm, Phonemes, Voice Quality.* John Benjamins.

Urassa, M., Lawson, D. W., Wamoyi, J., Gurmu, E., Gibson, M. A., Madhivanan, P., & Placek, C. (2021). Cross-cultural research must prioritize equitable collaboration. *Nature Human Behaviour*, *5*(6), Article 6. https://doi.org/10.1038/s41562-021-01076-x

Valentova, J. V., Tureček, P., Varella, M. A. C., Šebesta, P., Mendes, F. D. C., Pereira, K. J., Kubicová, L., Stolařová, P., and Havlíček, J. (2019). Vocal parameters of speech and singing covary and are related to vocal attractiveness, body measures, and sociosexuality: A cross-cultural study. *Frontiers in Psychology, 10*, 2029. https://doi.org/10.3389/fpsyg.2019.02029

Vanden Bosch der Nederlanden, C.M., Qi, X., Sequeira, S., Seth, P., Grahn, J.A., Joanisse, M.F., and Hannon, E.E. (2022). Developmental changes in the categorization of speech and song. *Developmental Science*, e13346. https://doi.org/10.1111/desc.13346

Vargha, A., & Delaney, H. D. (1998). The Kruskal-Wallis Test and Stochastic Homogeneity. *Journal of Educational and Behavioral Statistics*, *23*(2), 170–192. https://doi.org/10.3102/10769986023002170

Verhoef, T., & Ravignani, A. (2021). Melodic Universals Emerge or Are Sustained Through Cultural Evolution. *Frontiers in Psychology*, *12*. https://www.frontiersin.org/article/10.3389/fpsyg.2021.668300

Villing, R. (2010). *Hearing the Moment: Measures and Models of the Perceptual Centre* [Phd, National University of Ireland Maynooth]. https://mural.maynoothuniversity.ie/2284/

Vos, J., & Rasch, R. (1981). The perceptual onset of musical tones. *Perception & Psychophysics*, *29*(4), 323–335. https://doi.org/10.3758/BF03207341

Wang, Y., & Tian, L. (2018). An efficient numerical algorithm for exact inference in meta analysis. *Journal of Statistical Computation and Simulation*, *88*(4), 646–656. https://doi.org/10.1080/00949655.2017.1402331

Watanabe, S. (2018). *Mathematical Theory of Bayesian Statistics*. Chapman and Hall/CRC. https://doi.org/10.1201/9781315373010

Weber, F., Knapp, G., Ickstadt, K., Kundt, G., & Glass, Ä. (2020). Zero-cell corrections in random-effects meta-analyses. *Research Synthesis Methods*, *11*(6), 913–919. https://doi.org/10.1002/jrsm.1460

Wilson, D. J. (2019). The harmonic mean p-value for combining dependent tests. *Proceedings of the National Academy of Sciences*, *116*(4), 1195–1200. https://doi.org/10.1073/pnas.1814092116

Wood, A., Kirby, K. R., Ember, C., Silbert, S., Passmore, S., Daikoku, H., Mcbride, J., Paulay, F., Flory, M., Szinger, J., D'Arcangelo, G., Bradley, K. K., Guarino, M. F., Atayeva, M., Rifkin, J., Baron, V., Hajli, M. E., Szinger, M., & Savage, P. E. (2022). *The Global Jukebox: A public database of performing arts and culture. PLOS ONE 17(11), e0275469. https://doi.org/10.1371/journal.pone.0275469*

Zhang, R., & Ghanem, R. (2021). Normal-Bundle Bootstrap. *SIAM Journal on Mathematics of Data Science*, *3*(2), 573–592. https://doi.org/10.1137/20M1356002

4. Conclusion: Future directions for cultural evolutionary study of human acoustic communication.

In this dissertation, firstly, I reviewed the literature on the cultural evolution of music and language, and discussed some promising directions to jointly investigate the evolution of music and language. Within the concluding chapter, I outline potential avenues for future research on the evolutionary analysis of music and language. Furthermore, how global collaboration can make our scientific knowledge about music and language is also discussed.

4.1. Further research on the evolutionary analysis of music and language

4.1.1. Beyond cultural evolution

Although Chapter 2 targets cultural evolution, a more integrative approach would be to connect this area with the research on musicality (Honing et al., 2015) and linguisticality (Haspelmath, 2020), which are biological building blocks for producing and perceiving music and language, respectively. Cultural evolution helps us construct theories and patterns for how music and language evolve, but the understanding of its biological mechanisms and cross-species comparisons are needed to answer the question of where music and language came from.

Regarding the origins of music, various hypotheses have been proposed, such as social bonding (Savage et al., 2021), credible signaling (Mehr et al., 2021), sexual selection (Miller, 2000), and a byproduct of preceding traits, primarily language (Pinker, 1997). Although none of the hypotheses addressing adaptive values of music seem to be dominant, we can still advance theories regarding evolutionary specialization (Patel, forthcoming). In this regard, Patel (2021) hypothesizes that highly capable vocal learning ability induced the evolution of beat perception and synchronization abilities later, which are essential and widely exploited musical traits. He further suggests this evolution took the form of gene-culture co-evolution that music-like behaviors were adopted in populations for some reasons and that drove the selection of beat perception and synchronization abilities, then the prevalence of music-like behaviors further expanded, and so on.

But how can cultural evolution be coupled with such biological discussions? For example, although these experiments took place with today's humans who already acquired the faculty to perceive and synchronize with beats, several studies showcased how cultural evolutionary processes can generate musical rhythm patterns from scratch (Jacoby et al., 2021; Ravignani et al., 2016). What led our ancestors to adopt music-like behaviors remains a mystery, but perhaps even an early, crude beat perception capability could bias sporadic sound interval patterns to be organized rhythms, assuming such rhythms bring favorable effects to populations. Indeed, even a weak cognitive bias in individuals can easily determine population-level outcomes through cultural evolutionary processes (Mesoudi, 2016), and this is actually the case for structural universals of language (Kirby et al., 2007). Such amplification of weak biases has not been experimented with in music, but this experiment can potentially serve as a test for how the above scenario is likely. Though how this fits for music evolution is unclear at this moment, it would be worth remembering that gene-culture co-evolution can also happen by epigenetic effects (Ragsdale & Foley, 2022). In summary, fusing findings and evidence from both the papers on cultural evolution and biological evolution is necessary to further make progress in this research arena. The same argument can also be made for language evolution.

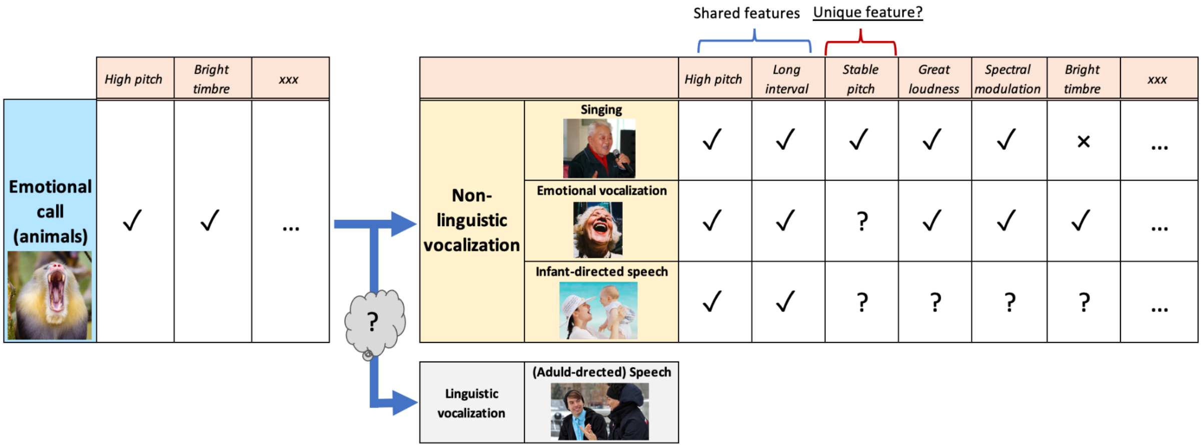
4.1.2. High pitch, low temporal rate, and stable pitch in acoustic communication

In the Discussion section of Chapter 3, we briefly discussed how three differentiating features, namely pitch height, temporal rate, and pitch stability connect to the evolutionary origin of music. Here, I attempt to develop a more specific, intermediate theory bridging our confirmatory predictions and the ultimate-level hypothesis based on the current result. One of the hypothesized functional origins of music is to communicate emotional states (Benítez-Burraco & Nikolsky, 2023; Jackendoff, 2009; Leongómez et al., 2022; Ma et al., 2019; Perlovsky, 2010; Snowdon et al., 2015; Trehub et al., 1997; and cf. S2 for detailed discussions), and I will draw commonalities between our findings and the related literature.

Anikin (2020) analyzed that high pitch, long duration, and high spectral modulation (potentially correlating with stable pitch [Albouy et al., 2020; 2023]) make more emotional vocalization salient. Their analysis and our result are congruent if we interpret music as also a part of vocalization expressing emotions. In addition, the use of higher pitch and slower sound production is also cross-culturally observed in infant-directed speech (Cox et al., 2022; Hilton et al., 2022). But we can also cast this phenomenon in the same framework with the following logic. If we want to communicate with infants who have not yet acquired their mother tongues, we certainly need to make use of communication elements that is neither referential nor linguistic, which may nudge us to employ acoustic cues effective for mental state communication.

Song, emotional vocalization, and infant-directed speech all appear in different contexts, but they have the shared characterizing features, and all of them include salient non-verbal aspects. In non-human animals, vocalization pattern is considered to co-evolve with social complexity to enable to reduce of uncertainty in individuals arising from various differentiated relationships (Cheney & Seyfarth, 2018; Fichtel & Kappeler, 2022; Freeberg et al., 2012; Schamberg et al., 2018). Combining this theory from ethology and commonalities among three types of vocalizations, I hypothesize song was specialized from (potentially non-linguistic) preceding emotional vocalizations by utilizing pitch information for affective states in response to function in specific relationships which emerged as human society became complex. For example, Mehr et al. (2019) identified that songs are associated with specific social contexts, namely love, healing, dance, and lullaby, widely across societies. Such contexts also entail unique relationships (e.g. patient and healer when healing but companions when dancing), and song was added to our vocalization repertoire as an effective tool to share affective states in various complex relationships as they appear in the society. This hypothesis can be considered a more specific version of the social bonding hypothesis (Savage et al., 2021).

Darwin (1871) already considered that emotional vocal expression is shared across species, so it has an evolutionary root. Based on Dawrwin's hypothesis, Filippi et al. (2017) tested whether human subjects can identify high arousal vocalization produced by a variety of terrestrial vertebrate animals. They found not only participants could recognize high arousal vocalization by animal, but also higher fundamental frequency functioned as a reliable predictor. However, whether a longer sound duration is useful depends on the species. A similar finding is also reported by Schamberg et al. (2018), so amongst the three features differentiating song and speech found in our study (i.e. higher pitch height, lower temporal rate, and higher pitch stability in song than speech), at least the use of high fundamental frequency for emotive communication can be rooted back to our ancestral communication practice. However, music is considered to communicate affects that may not be the same as basic emotions (Cespedes-Guevara & Eerola, 2018; Cowen et al., 2020). Therefore, acoustic properties observed in singing can be attributed to a more specific type of internal states. Nevertheless, the commonality that infant-directed speech and human emotional vocalizations also use higher pitch and longer duration suggests that humans rely on certain acoustic cues when referential information is not a primary communicative purpose, which may have been possibly inherited from the same root of ancestral vocalization for conveying emotive/internal states (cf. Figure 4.1).



	High pitch	Bright timbre	xxx
Emotional call (animals)	✓	✓	…

		High pitch	Long interval	Stable pitch	Great loudness	Spectral modulation	Bright timbre	xxx
Non-linguistic vocalization	Singing	✓	✓	✓	✓	✓	×	…
	Emotional vocalization	✓	✓	?	✓	✓	✓	…
	Infant-directed speech	✓	✓	?	?	?	?	…

Linguistic vocalization	(Aduld-drected) Speech

Figure 4.1. Illustration of the expansion of non-linguistic vocalization and the speciation into singing. The features differentiating song and speech identified in Chapter 3 have some overlap with other non-linguistic vocalizations and emotional calls by animals. The figure illustrates a hypothesis that singing is a particular form of vocalization conveying emotive/internal states rather than propositional/referential meaning, which has been speciated from an ancestral broader category. What acoustic features make singing unique in human acoustic communication can be further examined by comparing non-linguistic vocalization. This hypothesis does not assume that emotional call also evolved to communication for propositional/referential meaning (i.e., linguistic communication) as in the music proto-language hypothesis (Brown, 2000; Darwin, 1871; Fitch, 2010), considering their functional difference.

Our neural mechanism involved in speech and music processing is also in line with this claim. Fujii & Wan (2014) summarized the shared and distinctive neural pathways for rhythm perception and production of music and speech developed on Patel's OPERA hypothesis (Patel, 2011), and their model suggests that the subcortical-prefrontal circuit, which handles emotional and reward-related processing, only appears in music domain in contrast with rhythm perception and production in speech. Similarly, evidence from neuroimaging studies of individuals with autism spectrum disorder demonstrates their preserved ability to process the emotional aspects of music with activation of subcortical-prefrontal areas, despite their socio-emotional impairment in daily life (Caria et al., 2011; Koelsch, 2014; Lai et al., 2012). Taking together, it is likely that the acoustic cues we employ when making music function in a distinctive way that our brain links to emotions. Whether our findings regarding high pitch, low temporal rate, and stable pitch as key features that elicit emotional information in brain will be determined in future studies.

Singing exhibits unique acoustic structures compared to infant-directed speech and emotional vocalizations, and probably pitch stability would contribute to occupying a distinctive niche in the design space of human vocalization. Although why this feature is selected is elusive, it would be interesting to consider testing whether it is neutrally selected or it is due to some selection pressures. It is also attractive to analyze whether pitch stability has any relationship with pitch-related musicality and related hypotheses, like invariance of melody recognition by transposition in humans (Patel, 2019). Regarding pitch height, the cross-species study and phylogenetic comparative analysis suggest that the evolution of sensitivity to high-frequency range vocal calls is driven by social complexity (Ramsier et al., 2012), and coevolution of both production and perception of high-frequency vocalization occurred in mammals inhabiting forest environments (Charlton et al., 2019). These findings could serve as a starting point for formulating hypotheses regarding the origin of the use of high-frequency in our particular vocal communication forms. An increase in variations in vocalization patterns in tandem with the increase in social complexity has already been confirmed in several non-human animals, and one promising extension of this theory would be to consider testing this hypothesis for humans either in the field or experimentally to see if it drives the emergence of singing-like vocalization.

4.2. Global collaboration for music and language science

In order to derive a more general scientific statement about music and language, it is essential to include data sampled from societies as diverse as possible. This imposes a challenge for data collection and even sometimes data preprocessing or feature extraction due to a lack of cross-culturally consistent measurement (e.g. onset annotation discussed in Chapter 3). This situation strongly encourages researchers to build a global and inclusive collaboration so that the research can mitigate cultural bias in their data, methods, results, and interpretations. Such a practice also contributes to tackling exploitive, unfair scientific conducts such as helicopter research (Adame, 2021).

The social, behavioral, psychological, and cognitive sciences have employed creative approaches to recruit participants and gather data from a wider range of populations, such as the utilization of discipline-wide online infrastructures (Sheskin et al., 2020), the incorporation of gamification techniques (Long et al., 2023), and the integration of citizen science practices (Hilton & Mehr, 2022). Another effective approach would be 'big team' science (Coles et al., 2022), which allies many researchers on a single project. This aligns with the approach we adopted for the study of Chapter 3. Formulating a transparent policy stipulating the criteria for authorship and clarifying the expected roles/commitments of each collaborator is crucial to managing the process in this situation. In the study of Chapter 3, we have collaborated with dozens of academics and musicians to collect recordings and created an agreement form to make it explicit what we want them to contribute and how they will be rewarded. In the realm of music and language science, such a collective and inclusive approach may become more indispensable than ever. In fact, it would have been impossible for us to include recordings from various indigenous people communities in our hypothesis tests without collaboration with them. Nevertheless, it is noteworthy to mention that what we really need to care about on top of linguistic and cultural diversity is the diversity of participant demographics, such as age, income-level, and education. Merely collecting data from across different cities may not necessarily assure the desired quality (Ghai et al., 2023).

Regarding music, scholars have documented the cases that the Western word or concept "music" is not necessarily translatable to other societies (Nattiez, 1987/2005), which implies what audio recordings to be sampled for the study can potentially be biased by the viewpoint of the researcher of what they think "music" is. The lack of a universal definition of music suggests that we need to work collaboratively to reflect the diversity of "humanly organized sound" (Blacking, 1973/1978) and to realize equity in music science, even if it is still far from perfect.

During the song-speech project (Ch. 3), several challenges arose due to the nature of a large global-scale collaboration. Some collaborators from Brazilian indigenous communities, including the Yanomami people, had to withdraw from the project, likely due to an imminent issue imposed on their communities. This issue pertained to a serious health concern caused by mercury contamination resulting from illegal gold mining conducted in their areas (Nicas, 2023). Including data from indigenous people is arguably important. However, this issue highlights that such attempts are sometimes hampered by complex social and political matters surrounding them, which they need to prioritize over academic activities.

Another issue brought up by collaboration with diverse cultural backgrounds is the challenge of translating a concept developed in one culture to people from different cultures. This issue became apparent when we asked some collaborators to make a recording of the onset of singing through clapping or tapping. Since they did not have melodic instruments to play, we requested that these collaborators provide clapping/tapping recordings instead. Certain collaborators indeed made recordings as we expected, while the other collaborators played percussion or clapped as if they were accompanying the song with their traditional percussive instruments, just as it would be done in the original performance context. This mismatch likely occurred because of a lack of practice in playing the melody of the song using instruments from their own tradition, so they perhaps did not have an idea about playing instruments to imitate singing. In the end, we could have managed to collect the desired recordings by providing examples to them, which helped to communicate more clearly the types of recordings we were seeking. However, this communication gap made us realize what we initially called music was concerned with a melody- or pitch-oriented perspective. Thus we did not decide to include "music" in the title but opted for more specific terms ("songs and instrumental melodies").

Finally, I would also like to share the logistical and operational challenges that came with our global collaboration. These were also a necessary cost of promoting equity and inclusivity in music and language science, which we had to overcome. For example, honoraria to coauthors proved to be costly in terms of both finances and time. Each honorarium incurred an international wire transfer fee, and the paperwork required for cross-border payments usually becomes more complex and time-consuming. Another example is the complexity of using culturally unbiased terms as possible when creating a recording protocol. In Ch. 3, we frequently referred to the term acoustic unit, which represents an abstract concept of a unit of sound perceived in recordings. Initially, we considered using more common terms such as syllables or notes, but we also realized syllable is not necessarily universal for every language. Meanwhile, "note" was found to be ambiguous, and some coauthors first associated it with a unit appearing in Western staff notation, which is questionable to equally apply to songs collected from diverse societies. To address these concerns, we had to resort to a more general and abstract concept, leading us to use the term acoustic units (and P-centers). However, we acknowledge this decision made the protocol somewhat complex, and that in turn may have resulted in somewhat increased communication costs among collaborators. Incidentally, although this is general in projects involving a large number of members, communication costs escalate significantly as the team size grows. Therefore, making a protocol straight to every collaborator is crucial, though we encountered a situation asking over ten collaborators to re-record their recordings due to a misunderstanding of the protocol despite our best efforts to make it clear. Last but not least, of course, the recruitment of collaborators itself was also a demanding task. We utilized various channels such as a mailing list of the academic society, recruitment in a conference, and advertisement on Twitter to reach out to individuals who might be interested in participating in this project. The efforts required for these activities are far from negligible, but they must be prioritized to realize diversity in cultural and linguistic backgrounds within the team.

Inclusive and global collaboration would be increasingly important for building novel scientific knowledge. Allying with researchers from multiple societies and countries have some general challenges, in addition to the above-mentioned specific cases, such as language barrier (Khelifa et al., 2022) and limited funding usable for international or multi-national projects (Matthews et al., 2020). However, as large-scale collaboration becomes more recognized as an effective strategy to advance scientific missions, discussions on these issues will gain more attention and become more active, which will hopefully lead to deriving working solutions from there.

4.3. Reflection on the use of Registered Reports

Lastly, although this is not directly related to music and language research, I would like to write about Registered Reports (Center for Open Science, n.d.; Henderson & Chambers, 2022) in the hope of inspiring readers to take into consideration this recently growing yet still not fully recognized research practice by sharing what I could have gained from it. I have used Registered Reports two times for my research projects (Ch. 3; Chiba et al., 2023). An organization called Peer Community In Registered Reports (PCI-RR) manages the review of this publication framwork. This framework values the quality of hypothesis building and the approach to hypothesis testing, thereby effectively disciplining projects by separating activities between the planning phase and execution phase. In Registered Reports, acceptance of the manuscript is principally determined by the quality of the research plan rather than the results. Therefore, it naturally directed our attention towards sophisticating predictions and how to effectively test them. In fact, we could have established a rigorous prediction and protocol to verify it in my research projects thanks to adopting this framework. However, in our song-speech project, we have actually treated the significance of the results from rigorously planned confirmatory analyses and ad-hoc exploratory analyses almost equally. The appropriateness of this treatment, in terms of hindsight bias, may be questioned, and there may be some lessons to be learned from it.

In light of collaborative research, Registered Reports can potentially be used to precisely control research activities assigned to each collaborator or research site (e.g., Coles et al., 2022). We have also created a recording protocol that outlines the steps to be followed by all collaborators during the data collection stage, ensuring transparency. Involving multiple collaborators can make the project activity complex and potentially ambiguous. Registered Reports can serve as a means to keep the study open and traceable in such a situation.

Registered Reports have further advantages, in addition to preventing publication bias, when compared to a traditional review process. One notable advantage is that authors can obtain reviews and feedback at the planning stage. This would undoubtedly help improve the solidity of hypotheses, experimental paradigm, sample selection strategy, and analysis methods, all of which are crucial factors in making research successful. In the traditional publication process, researchers receive reviews after completing every research, which is often too late to detect potential flaws embedded in the study design. In our cases, the sight-vs-sound project (Chiba et al., 2023) indeed greatly benefited from the Registered Reports review process. While the core part of the hypotheses remained the same, we made extensive updates to the experimental design and analysis plan based on the feedback received during the Stage 1 review process. Although we may never know how the project ended up if we had proceeded with the original research design, we are confident that the revised version is more sound. The same applies to the song-speech project. Several exploratory analyses and robustness checks were incorporated based on the Stage 1 reviews, which certainly contributed to increasing the validity of our main results by addressing potential criticisms with the added analysis plan.

Another advantage of Registered Reports is that it provides a scheduled review process. In this process, authors first submit a single-page summary of the study, known as a snapshot, to PCI-RR editors. The editors then organize reviewers based on the content provided in the snapshot, taking into consideration the time limit for the review process, which is a maximum of six weeks. Although this process is not available for the Stage 2 review, which is primarily the confirmation of whether the study adhered to the plan specified at the Stage 1 review, it is an effective scheme to expedite the most arduous part of the Registered Reports review. We utilized the scheduled review in the song-speech project, which helped us initiate the project to fit its timeline for my PhD programme.

How the use of Registered Reports is beneficial may vary depending on the type of study and field, and whether the acceptance by PCI-RR has the same utility as acceptance by journals may also be contingent on the researcher's circumstances. Nevertheless, it is worth considering, and Registered Reports arguably offer unique merits, as described in this section and examplified by how it worked in my own PhD experience.

4.4. Summary

Music and language are so diverse yet omnipresent in our societies, and they are a part of our cultures inherited from generation to generation. Still, much scientific work has to be done to answer the following central questions that I worked on in this dissertation: Where do music and language come from? What do make music and language so special for us? I hope my work contributes to building novel knowledge about music and language around the world.

References

Adame, F. (2021). Meaningful collaborations can end 'helicopter research.' *Nature*. https://doi.org/10.1038/d41586-021-01795-1

Albouy, P., Benjamin, L., Morillon, B., & Zatorre, R. J. (2020). Distinct sensitivity to spectrotemporal modulation supports brain asymmetry for speech and melody. *Science*, *367*(6481), 1043–1047. https://doi.org/10.1126/science.aaz3468

Albouy, P., Mehr, S. A., Hoyer, R. S., Ginzburg, J., & Zatorre, R. J. (2023). *Spectro-temporal acoustical markers differentiate speech from song across cultures* (p. 2023.01.29.526133). bioRxiv Preprint. https://doi.org/10.1101/2023.01.29.526133

Anikin, A. (2020). The link between auditory salience and emotion intensity. *Cognition and Emotion*, *34*(6), 1246–1259. https://doi.org/10.1080/02699931.2020.1736992

Benítez-Burraco, A., & Nikolsky, A. (2023). The (Co)Evolution of Language and Music Under Human Self-Domestication. *Human Nature*. https://doi.org/10.1007/s12110-023-09447-1

Blacking, J. (1978). *How Musical Is Man?* (Y. Tokumaru, Trans.) Iwanami-Gendai-Sensho (岩波現代選書). https://uwapress.uw.edu/book/9780295953380/how-musical-is-man (Original work published 1973)

Brown, S. (2000). The Musilanguage Model of Music Evolution. In S. Brown, B. Merker, & C. Wallin (Eds.), *The Origins of Music* (pp. 271–300). The MIT Press. https://direct.mit.edu/books/book/2109/chapter/56564/The-Musilanguage-Model-of-Music-Evolution

Caria, A., Venuti, P., & de Falco, S. (2011). Functional and Dysfunctional Brain Circuits Underlying Emotional Processing of Music in Autism Spectrum Disorders. *Cerebral Cortex*, *21*(12), 2838–2849. https://doi.org/10.1093/cercor/bhr084

Center for Open Science. (n.d.). *Registered Reports*. Retrieved June 25, 2023, from https://www.cos.io/initiatives/registered-reports

Cespedes-Guevara, J., & Eerola, T. (2018). Music Communicates Affects, Not Basic Emotions – A Constructionist Account of Attribution of Emotional Meanings to Music. *Frontiers in Psychology*, *9*. https://www.frontiersin.org/articles/10.3389/fpsyg.2018.00215

Charlton, B. D., Owen, M. A., & Swaisgood, R. R. (2019). Coevolution of vocal signal characteristics and hearing sensitivity in forest mammals. *Nature Communications*, *10*(1), Article 1. https://doi.org/10.1038/s41467-019-10768-y

Cheney, D. L., & Seyfarth, R. M. (2018). Flexible usage and social function in primate vocalizations. *Proceedings of the National Academy of Sciences*, *115*(9), 1974–1979. https://doi.org/10.1073/pnas.1717572115

Chiba, G., Ozaki, Y., Fujii, S., & Savage, P. E. (2023). Sight vs. Sound Judgments of Music Performance Depend on Relative Performer Quality: Cross-cultural Evidence From Classical Piano and Tsugaru Shamisen Competitions. *Collabra: Psychology*, *9*(1), 73641. https://doi.org/10.1525/collabra.73641

Coles, N. A., Hamlin, J. K., Sullivan, L. L., Parker, T. H., & Altschul, D. (2022). Build up big-team science. *Nature*, *601*(7894), 505–507. https://doi.org/10.1038/d41586-022-00150-2

Coles, N. A., March, D. S., Marmolejo-Ramos, F., Larsen, J. T., Arinze, N. C., Ndukaihe, I. L. G., Willis, M. L., Foroni, F., Reggev, N., Mokady, A., Forscher, P. S., Hunter, J. F., Kaminski, G., Yüvrük, E., Kapucu, A., Nagy, T., Hajdu, N., Tejada, J., Freitag, R. M. K., … Liuzza, M. T. (2022). A multi-lab test of the facial feedback hypothesis by the Many Smiles Collaboration. *Nature Human Behaviour*, 6(12), Article 12. https://doi.org/10.1038/s41562-022-01458-9

Cowen, A. S., Fang, X., Sauter, D., & Keltner, D. (2020). What music makes us feel: At least 13 dimensions organize subjective experiences associated with music across different cultures. *Proceedings of the National Academy of Sciences*, *117*(4), 1924–1934. https://doi.org/10.1073/pnas.1910704117

Cox, C., Bergmann, C., Fowler, E., Keren-Portnoy, T., Roepstorff, A., Bryant, G., & Fusaroli, R. (2022). A systematic review and Bayesian meta-analysis of the acoustic features of infant-directed speech. *Nature Human Behaviour*, 1–20. https://doi.org/10.1038/s41562-022-01452-1

Darwin, C. (1871). *The descent of man*. Watts & Co.

Fitch, W. T. (2010). *The Evolution of Language*. Cambridge University Press. https://doi.org/10.1017/CBO9780511817779

Fichtel, C., & Kappeler, P. M. (2022). Coevolution of social and communicative complexity in lemurs. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *377*(1860), 20210297. https://doi.org/10.1098/rstb.2021.0297

Filippi, P., Congdon, J. V., Hoang, J., Bowling, D. L., Reber, S. A., Pašukonis, A., Hoeschele, M., Ocklenburg, S., de Boer, B., Sturdy, C. B., Newen, A., & Güntürkün, O. (2017). Humans recognize emotional arousal in vocalizations across all classes of terrestrial vertebrates: Evidence for acoustic universals. *Proceedings of the Royal Society B: Biological Sciences*, *284*(1859), 20170990. https://doi.org/10.1098/rspb.2017.0990

Freeberg, T. M., Dunbar, R. I. M., & Ord, T. J. (2012). Social complexity as a proximate and ultimate factor in communicative complexity. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *367*(1597), 1785–1801. https://doi.org/10.1098/rstb.2011.0213

Fujii, S., & Wan, C. Y. (2014). The Role of Rhythm in Speech and Language Rehabilitation: The SEP Hypothesis. *Frontiers in Human Neuroscience*, *8*. https://www.frontiersin.org/articles/10.3389/fnhum.2014.00777

Ghai, S., Forscher, P. S., & Chuan-Peng, H. (2023). *The illusion of generalizability in one big team science study*. PsyArXiv. https://doi.org/10.31234/osf.io/avcsp

Henderson, E. L., & Chambers, C. D. (2022). Ten simple rules for writing a Registered Report. *PLOS Computational Biology*, 18(10), e1010571. https://doi.org/10.1371/journal.pcbi.1010571

Haspelmath, M. (2020). Human Linguisticality and the Building Blocks of Languages. *Frontiers in Psychology*, *10*. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.03056

Hilton, C. B., & Mehr, S. A. (2022). Citizen science can help to alleviate the generalizability crisis. *Behavioral and Brain Sciences*, *45*, e21. https://doi.org/10.1017/S0140525X21000352

Hilton, C. B., Moser, C. J., Bertolo, M., Lee-Rubin, H., Amir, D., Bainbridge, C. M., Simson, J., Knox, D., Glowacki, L., Alemu, E., Galbarczyk, A., Jasienska, G., Ross, C. T., Neff, M. B., Martin, A., Cirelli, L. K., Trehub, S. E., Song, J., Kim, M., … Mehr, S. A. (2022). Acoustic regularities in infant-directed speech and song across cultures. *Nature Human Behaviour*, *6*(11), Article 11. https://doi.org/10.1038/s41562-022-01410-x

Honing, H., ten Cate, C., Peretz, I., & Trehub, S. E. (2015). Without it no music: Cognition, biology and evolution of musicality. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1664), 20140088. https://doi.org/10.1098/rstb.2014.0088

Jackendoff, R. (2009). Parallels and Nonparallels between Language and Music. *Music Perception: An Interdisciplinary Journal*, *26*(3), 195–204. https://doi.org/10.1525/mp.2009.26.3.195

Jacoby, N., Polak, R., Grahn, J., Cameron, D. J., Lee, K. M., Godoy, R., Undurraga, E. A., Huanca, T., Thalwitzer, T., Doumbia, N., Goldberg, D., Margulis, E., Wong, P. C. M., Jure, L., Rocamora, M., Fujii, S., Savage, P. E., Ajimi, J., Konno, R., … McDermott, J. H. (2021). *Universality and cross-cultural variation in mental representations of music revealed by global comparison of rhythm priors*. PsyArXiv preprint. https://doi.org/10.31234/osf.io/b879v

Khelifa, R., Amano, T., & Nuñez, M. A. (2022). A solution for breaking the language barrier. *Trends in Ecology & Evolution*, *37*(2), 109–112. https://doi.org/10.1016/j.tree.2021.11.003

Kirby, S., Dowman, M., & Griffiths, T. L. (2007). Innateness and culture in the evolution of language. *Proceedings of the National Academy of Sciences*, *104*(12), 5241–5245. https://doi.org/10.1073/pnas.0608222104

Koelsch, S. (2014). Brain correlates of music-evoked emotions. *Nature Reviews Neuroscience*, *15*(3), Article 3. https://doi.org/10.1038/nrn3666

Lai, G., Pantazatos, S. P., Schneider, H., & Hirsch, J. (2012). Neural systems for speech and song in autism. *Brain*, *135*(3), 961–975. https://doi.org/10.1093/brain/awr335

Leongómez, J. D., Havlíček, J., & Roberts, S. C. (2022). Musicality in human vocal communication: An evolutionary perspective. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *377*(1841), 20200391. https://doi.org/10.1098/rstb.2020.0391

Long, B., Simson, J., Buxó-Lugo, A., Watson, D. G., & Mehr, S. A. (2023). How games can make behavioural science better. *Nature*, *613*(7944), 433–436. https://doi.org/10.1038/d41586-023-00065-6

Ma, W., Fiveash, A., & Thompson, W. F. (2019). Spontaneous emergence of language-like and music-like vocalizations from an artificial protolanguage. *Semiotica*, *2019*(229), 1–23. https://doi.org/10.1515/sem-2018-0139

Matthews, K. R. W., Yang, E., Lewis, S. W., Vaidyanathan, B. R., & Gorman, M. (2020). International scientific collaborative activities and barriers to them in eight societies. *Accountability in Research*, *27*(8), 477–495. https://doi.org/10.1080/08989621.2020.1774373

Mehr, S. A., Singh, M., Knox, D., Ketter, D. M., Pickens-Jones, D., Atwood, S., Lucas, C., Jacoby, N., Egner, A. A., Hopkins, E. J., Howard, R. M., Hartshorne, J. K., Jennings, M. V., Simson, J., Bainbridge, C. M., Pinker, S., O'Donnell, T. J., Krasnow, M. M., & Glowacki, L. (2019). Universality and diversity in human song. *Science*, *366*(6468), eaax0868. https://doi.org/10.1126/science.aax0868

Mehr, S. A., Krasnow, M. M., Bryant, G. A., & Hagen, E. H. (2021). Origins of music in credible signaling. *Behavioral and Brain Sciences*, *44*. https://doi.org/10.1017/S0140525X20000345

Mesoudi, A. (2016). Cultural Evolution: A Review of Theory, Findings and Controversies. *Evolutionary Biology*, *43*(4), 481–497. https://doi.org/10.1007/s11692-015-9320-0

Miller, G. (2000). Evolution of human music through sexual selection. In N. L. Wallin, B. Merker, & S. Brown (Eds.), *The origins of music* (pp. 329–360). The MIT Press.

Nattiez, J.-J. (2005) *Musicologie générale et sémiologie* (Y. Adachi, Trans.). 春秋社 (Shunjusha). (Original work published 1987)

Nicas, J. (2023, March 25). The Amazon's Largest Isolated Tribe Is Dying. *The New York Times*. https://www.nytimes.com/2023/03/25/world/americas/brazil-amazon-indigenous-tribe.html

Patel, A. (2011). Why would Musical Training Benefit the Neural Encoding of Speech? The OPERA Hypothesis. *Frontiers in Psychology*, *2*. https://www.frontiersin.org/articles/10.3389/fpsyg.2011.00142

Patel, A. D. (2019). Evolutionary music cognition: Cross-species studies. In: P. J. Rentfrow & D. Levitin (Eds.) *Foundations in Music Psychology: Theory and Research*. The MIT Press (pp. 459-501).

Patel, A. D. (2021). Vocal learning as a preadaptation for the evolution of human beat perception and synchronization. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1835), 20200326. https://doi.org/10.1098/rstb.2020.0326

Patel, A. D. (forthcoming). Musicality and gene-culture coevolution: ten concepts to guide productive exploration. In: E.H. Margulis, D. Loughridge, & P. Loui (Eds.) *The Science-Music Borderlands: Reckoning with the Past, Imagining the Future*. The MIT Press. (Preprint URL: https://psyarxiv.com/qp6jx/)

Perlovsky, L. (2010). Musical emotions: Functions, origins, evolution. *Physics of Life Reviews*, *7*(1), 2–27. https://doi.org/10.1016/j.plrev.2009.11.001

Pinker, S. (1997). *How the mind works*. New York: Norton.

Ragsdale, G., & Foley, R. A. (2022). Models of gene–culture evolution are incomplete without incorporating epigenetic effects. *Behavioral and Brain Sciences*, *45*, e174. https://doi.org/10.1017/S0140525X21001588

Ramsier, M. A., Cunningham, A. J., Finneran, J. J., & Dominy, N. J. (2012). Social drive and the evolution of primate hearing. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *367*(1597), 1860–1868. https://doi.org/10.1098/rstb.2011.0219

Ravignani, A., Delgado, T., & Kirby, S. (2016). Musical evolution in the lab exhibits rhythmic universals. *Nature Human Behaviour*, *1*(1), Article 1. https://doi.org/10.1038/s41562-016-0007

Savage, P. E., Loui, P., Tarr, B., Schachner, A., Glowacki, L., Mithen, S., & Fitch, W. T. (2021). Music as a coevolved system for social bonding. *Behavioral and Brain Sciences*, *44*. https://doi.org/10.1017/S0140525X20000333

Schamberg, I., Wittig, R. M., & Crockford, C. (2018). Call type signals caller goal: A new take on ultimate and proximate influences in vocal production. *Biological Reviews*, *93*(4), 2071–2082. https://doi.org/10.1111/brv.12437

Sheskin, M., Scott, K., Mills, C. M., Bergelson, E., Bonawitz, E., Spelke, E. S., Fei-Fei, L., Keil, F. C., Gweon, H., Tenenbaum, J. B., Jara-Ettinger, J., Adolph, K. E., Rhodes, M., Frank, M. C., Mehr, S. A., & Schulz, L. (2020). Online Developmental Science to Foster Innovation, Access, and Impact. *Trends in Cognitive Sciences*, *24*(9), 675–678. https://doi.org/10.1016/j.tics.2020.06.004

Snowdon, C. T., Zimmermann, E., & Altenmüller, E. (2015). Music evolution and neuroscience. In E. Altenmüller, S. Finger, & F. Boller (Eds.), *Progress in Brain Research* (Vol. 217, pp. 17–34). Elsevier. https://doi.org/10.1016/bs.pbr.2014.11.019

Trehub, S. E., Unyk, A. M., Kamenetsky, S. B., Hill, D. S., Trainor, L. J., Henderson, J. L., & Saraza, M. (1997). Mothers' and fathers' singing to infants. *Developmental Psychology*, *33*(3), 500–507. https://doi.org/10.1037/0012-1649.33.3.500

A. Stage 1 Supplementary Materials of Chapter 3

S1. Supplementary method

S1.1. Recording and segmentation protocol

In order to keep the quality and consistency of the recordings, we created a detailed recording protocol for coauthors to follow when recording (Appendix 1). The protocol gives detailed instructions for things like how to interpret the instructions to choose a “traditional song in their 1st or heritage language” for cases where they are multilingual; logistics such as recording duration (minimum 30s, maximum 5 minutes for the song and the spoken description), file format, and how to deliver recordings to a secure email account monitored by a Research Assistant who is not a coauthor on the manuscript. All recordings are made by the coauthor themselves singing/ speaking/ playing instruments.

In addition to the recordings, we also collect the texts of recordings which are segmented into acoustic units (e.g., notes, syllables) according to their perceptual center (P-center) (Danielsen et al., 2019; Howell, 1988; Morton et al., 1976; Pompino-Marschall, 1989; Scott, 1998; Vos & Rasch, 1981). Here, the P-center is defined as the moment sound is perceived to begin, and the P-center is considered to be able to capture the perceptual experience of rhythm (Scott, 1998; Villing, 2010). The segmentation by the P-center is expected to reflect the vocalizer’s perception of the beginning of acoustic units. Here, we use acoustic units as a general term that a listener perceives as a unit of sound sequences such as syllables and notes. However, some languages have their own linguistic unit (e.g. mora in Japanese) and music as well (Fushi 節 in Japanese traditional folk songs). It is challenging to identify the beginnings of acoustic units for different domains (e.g., language and music), musical traditions, and languages comprising different phonemic and suprasegmental properties. For example, the location of the P-center in speech is known to be dependent on various factors such as the duration of phonemic elements (e.g. vowel, consonant) and the type of the syllable-initial consonant (Barbosa et al., 2005; Chow et al., 2015; Cooper et al., 1986; Villing, 2010). Therefore, rather than building an objective definition of sound onset, we ask each participant to reflect on their interpretation of acoustic units of their song and speech focusing on the P-center. Segmented texts are used to create onset and breath annotations with SonicVisualizer software (Cannam et al., 2010; https://www.sonicvisualiser.org/) which will be the base of some features. SonicVisualizer was chosen because it provides a simple interface to add a click sound to the desired time location of the audio to reflect the P-center. Those annotations will be created by the first author (Ozaki) because the time required to train and ask each collaborator to create these annotations would not allow us to recruit enough collaborators for a well-powered analysis.

In order to maximize efficiency and quality in our manual annotations, we adopt the following 3-step process:

1) Each coauthor sends a text file segmenting their recorded song/speech into acoustic units and breathing breaks (see Appendix 1 for examples).
2) The first author (Ozaki) creates detailed millisecond-level annotations of the audio recording files based on these segmented texts. (This is the most time-consuming part of the process).
3) Each coauthor then checks Ozaki’s annotations (by listening to the recording with “clicks” added to each acoustic unit) and corrects them and/or has Ozaki correct them as needed until the coauthor is satisfied with the accuracy of the annotation.

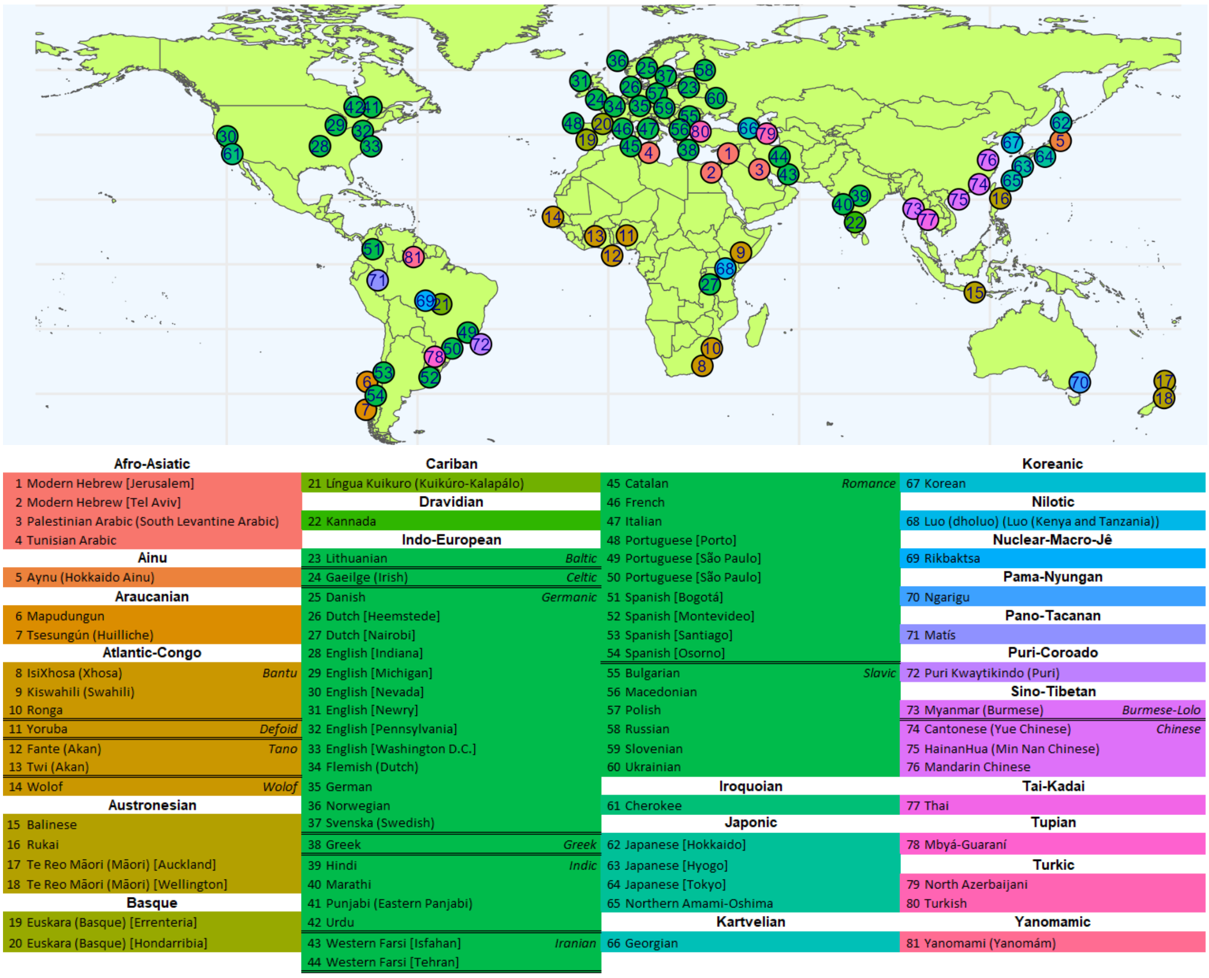
S1.2. Language sample

S1.2.1. Inclusion criteria

All audio recordings analyzed are made by our group of 81 coauthors recording ourselves singing/speaking in our 1st/heritage languages, which span 23 language families (Fig. S1). Coauthors were chosen by opportunistic sampling beginning from co-corresponding author Savage's network of researchers, a public call to the email list of the International Council for Traditional Music (July 15 2022 to ictm-l@ictmusic.org; cf. Appendix 3), and recruitment at various conferences/symposia (International Council for Traditional Music, July 2022, Portugal; Joint Conference on Language Evolution, Sep 2022, Japan; Interdisciplinary Debates on the Empirical Aesthetics of Music series, Dec 2021, online; Social Bridges, Jan 2022, online; European Society for Cognitive Psychology, Feb 2022; AI Music Creativity, Sep 2022, online), with additional snowball recruitment from some collaborators using their own networks. Most authors are multilingual speakers who can speak English, though a few are multilingual in other languages (e.g., Portuguese, Japanese) with translations to and from English done by other coauthors as needed.

The set of linguistic varieties in this study represents a considerable portion of the world cross-linguistic variability in the main aspects that could conceivably play a role in shaping speech-song similarities/variabilities across languages (Dryer et al., 2013; https://wals.info/languoid):

- Head-complement order: languages with basic head-complement order (e.g. English), languages with basic complement-head order (e.g. Bengali)
- Vowel inventory size: moderate (e.g. Japanese), large (e.g. German)
- Consonant inventory size: small (e.g. Ainu), moderately small (e.g. Guaraní), average (e.g. Greek), moderately large (e.g. Swahili), large (e.g. Ronga)
- Consonant/vowel ratio: low (e.g. French), moderately low (e.g. Korean), average (e.g. Spanish), moderately high (e.g. Lithuanian), high (e.g. Russian)
- Potential syllable structures: simple (e.g. Yoruba), moderately complex (e.g. Catalan), complex (e.g. Kannada)
- Word-prosodic systems: stress-accent systems (e.g. Italian), pitch-accent systems (e.g. Swedish), tonal systems (e.g. Cantonese)
- Stress location: initial (e.g. Irish), postinitial (e.g. Basque), ante-penultimate (e.g. Georgian), penultimate (e.g. Polish), final (e.g. Balinese)
- Rhythm type: iambic (e.g. Mapudungun), trochaic (e.g. Hebrew)
- Complexity of tone systems: simple (e.g. Cherokee), complex (e.g. Thai)



Afro-Asiatic	**Cariban**		**Koreanic**
1 Modern Hebrew [Jerusalem]	21 Língua Kuikuro (Kuikúro-Kalapálo)	45 Catalan *Romance*	67 Korean
2 Modern Hebrew [Tel Aviv]	**Dravidian**	46 French	**Nilotic**
3 Palestinian Arabic (South Levantine Arabic)	22 Kannada	47 Italian	68 Luo (dholuo) (Luo (Kenya and Tanzania))
4 Tunisian Arabic	**Indo-European**	48 Portuguese [Porto]	**Nuclear-Macro-Jê**
Ainu	23 Lithuanian *Baltic*	49 Portuguese [São Paulo]	69 Rikbaktsa
5 Aynu (Hokkaido Ainu)	24 Gaeilge (Irish) *Celtic*	50 Portuguese [São Paulo]	**Pama-Nyungan**
Araucanian	25 Danish *Germanic*	51 Spanish [Bogotá]	70 Ngarigu
6 Mapudungun	26 Dutch [Heemstede]	52 Spanish [Montevideo]	**Pano-Tacanan**
7 Tsesungún (Huilliche)	27 Dutch [Nairobi]	53 Spanish [Santiago]	71 Matís
Atlantic-Congo	28 English [Indiana]	54 Spanish [Osorno]	**Puri-Coroado**
8 IsiXhosa (Xhosa) *Bantu*	29 English [Michigan]	55 Bulgarian *Slavic*	72 Puri Kwaytikindo (Puri)
9 Kiswahili (Swahili)	30 English [Nevada]	56 Macedonian	**Sino-Tibetan**
10 Ronga	31 English [Newry]	57 Polish	73 Myanmar (Burmese) *Burmese-Lolo*
11 Yoruba *Defoid*	32 English [Pennsylvania]	58 Russian	74 Cantonese (Yue Chinese) *Chinese*
12 Fante (Akan) *Tano*	33 English [Washington D.C.]	59 Slovenian	75 HainanHua (Min Nan Chinese)
13 Twi (Akan)	34 Flemish (Dutch)	60 Ukrainian	76 Mandarin Chinese
14 Wolof *Wolof*	35 German	**Iroquoian**	**Tai-Kadai**
Austronesian	36 Norwegian	61 Cherokee	77 Thai
15 Balinese	37 Svenska (Swedish)	**Japonic**	**Tupian**
16 Rukai	38 Greek *Greek*	62 Japanese [Hokkaido]	78 Mbyá-Guaraní
17 Te Reo Māori (Māori) [Auckland]	39 Hindi *Indic*	63 Japanese [Hyogo]	**Turkic**
18 Te Reo Māori (Māori) [Wellington]	40 Marathi	64 Japanese [Tokyo]	79 North Azerbaijani
Basque	41 Punjabi (Eastern Panjabi)	65 Northern Amami-Oshima	80 Turkish
19 Euskara (Basque) [Errenteria]	42 Urdu	**Kartvelian**	**Yanomamic**
20 Euskara (Basque) [Hondarribia]	43 Western Farsi [Isfahan] *Iranian*	66 Georgian	81 Yanomami (Yanomám)
	44 Western Farsi [Tehran]		

Figure S1. Map of the linguistic varieties spoken by our 81 coauthors as 1st/heritage languages. Each circle represents a coauthor singing and speaking in their 1st (L1) or heritage language. The geographic coordinates represent their hometown where they learned that language. In cases when the language name preferred by that coauthor (ethnonym) differs from the L1 language name in the standardized classification in the Glottolog (Hammarström et al., 2022), the ethnonym is listed first followed by the Glottolog name in round brackets. Language family classifications (in bold) are based on Glottolog. Square brackets indicate geographic locations for languages represented by more than one coauthor. Atlantic-Congo, Indo-European and Sino-Tibetan languages are further grouped by genus defined by the World Atlas of Language Structures (Dryer et al., 2013; https://wals.info/languoid).

S1.2.2. Exclusion criteria and data quality checks

If coauthors choose to withdraw their collaboration agreement at any point prior to formal acceptance after peer review, their recording set will be excluded (cf. Appendix 2). If their recording quality is too poor to reliably extract features, or if they fail to meet the formatting requirements in the protocol we will ask them to resubmit a corrected recording set. In order to keep ourselves as blind as possible to the data prior to In Principle Acceptance and analysis, we ask coauthors to send only their segmented texts, not their audio recordings, to coauthors Ozaki & Savage to conduct formatting checks (e.g., ensuring that coauthors had understood the instructions to make all recordings in the same language and to segment their sung/spoken texts into acoustic units), so that we will not need to access the audio recordings until after In Principle Acceptance.

After we had already begun this process, we decided to add an additional layer of formatting and data quality checks by hiring a Research Assistant (RA) who is not a coauthor to create and securely monitor an external email account where authors could send their audio recordings. This allows us to prevent data loss (e.g., collaborators losing computers or accidentally deleting files), as well as allowing us to have the RA confirm that recording quality was acceptable, recordings met minimum length requirements, etc. The RA will not share the account password needed to access these recordings with us until we have received In Principle Acceptance.

S1.3. Features

We will compare the following six features between song and speech for our main confirmatory analyses:

1) Pitch height (fundamental frequency (f_0)) [*Hz*],
2) Temporal rate (inter-onset interval (IOI) rate) [*Hz*],
3) Pitch stability (-|f_0|) [*cent/sec.*],
4) Timbral brightness (spectral centroid) [*Hz*],
5) Pitch interval size (f_0 ratio) [*cent*],
    - Absolute value of pitch ratio converted to the cent scale.
6) Pitch declination (sign of f_0 slope) [dimensionless]
    - Sign of the coefficient of robust linear regression fitted to the phrase-wise f_0 contour.

For each feature, we will compare its distribution in the song recording with its distribution in the spoken description by the same singer/speaker, converting their overall combined distributions into a single scalar measure of nonparametric standardized difference (cf. Fig. 2).

We selected these features by reviewing what past studies focused on for the analysis of song-speech comparison and prominently observed features in music (e.g. Fitch, 2006; Hansen et al., 2020; Hilton et al., 2022; Savage et al., 2015; Sharma et al., 2021, see the Supplementary Discussion section S2 for a more comprehensive literature review). Here, f_0, rate of change of f_0, and spectral centroid are extracted purely from acoustic signals, while IOI rate is based purely on manual annotations. Pitch interval size and pitch declination analyses combine a mixture of automated and manual methods (i.e. extracted f_0 data combined with onset/breath annotations). The details of each feature can be found in the supplementary materials. Note that some theoretically relevant features we explored in our pilot analyses (especially the "regular rhythmic patterns" from Lomax & Grauer's definition of song quoted in the introduction) proved difficult to quantify using existing metrics and thus are not included in our six candidate features (cf. Fig. S9 for pilot data and discussion for potential proxies that we found unsatisfactory such as "IOI ratio deviation" and "pulse clarity").

S1.4. Pilot data analysis

We collected recordings from five coauthors for pilot data analysis[3] Each speaks a different 1st language: English, Japanese, Farsi, Marathi, and Yoruba. Figure S2 uses the analysis framework shown in Fig. 2 to calculate relative effect sizes for all five recording sets for all six hypothesized features. Note that our inferential statistical analysis uses the relative effects, but we translate these to Cohen’s d in Fig. S2 for ease of interpretability, but technically our analysis is not the same as directly measuring Cohen’s d of the data.

The primary purpose of the pilot analysis is to demonstrate feasibility and proof of concept, but we also used it to help decide on our final set of six features to focus on for our confirmatory analyses (Fig. S2). A full pilot analysis including additional features that we decided not to test is shown in Fig. S9. However, while some of our hypotheses appear to be strongly supported by our pilot data (e.g., song consistently appears much higher and much slower than speech, and timbral brightness appears consistently similar), others seem more ambiguous (e.g., pitch stability and pitch interval size show similar, weak trends although we predict pitch stability to differ but pitch interval size not to differ). In these cases, we prioritized our theoretical predictions over the pilot data trends, as effect sizes estimated from pilot data are not considered reliable (Brysbaert, 2019), while ample theory predicts that song should use more stable pitches than speech (e.g., Fitch, 2006) but sung and spoken pitch interval size should be similar (e.g., Tierney et al., 2010). However, we will be less surprised if our predictions for pitch stability and pitch interval size are falsified than if our predictions for pitch height and temporal rate are. Summary statistics visualizing the data underlying Fig. S2 in a finer-grained way are shown in Figure S3.

[3] Coauthors who contributed pilot data also recorded separate recording sets to be used in the main confirmatory analysis to ensure our main analyses are not biased by reusing pilot data.

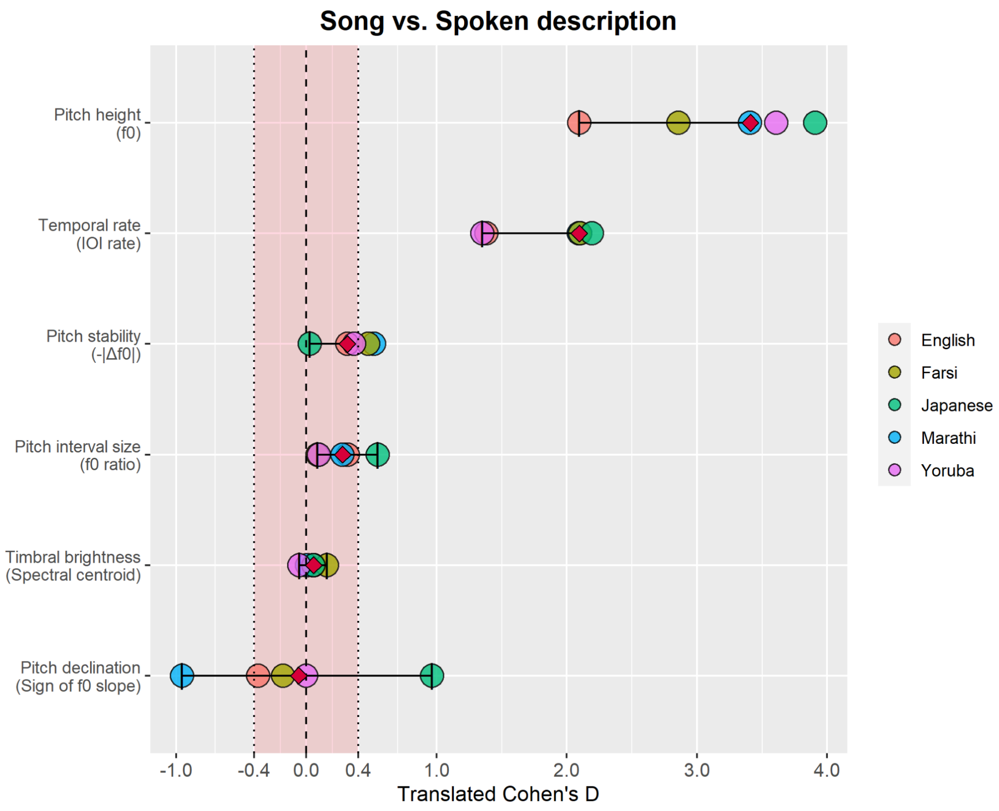


Figure S2. Pilot data showing similarities/differences between song and speech for each of the six hypothesized features across speakers of five languages (coauthors McBride, Hadavi, Ozaki, D. Sadaphal, and Nweke) Red diamonds indicate the population mean and black bars are confidence intervals estimated by the meta-analysis method. Although we use false discovery rate to adjust the alpha-level, these intervals are constructed based on Bonferroni corrected alpha (i.e. 0.05/6). Whether the confidence interval is one-sided or two-sided is determined by the type of the hypothesis. Positive effect sizes indicates song having a higher value than speech, with the exception of “temporal rate”, whose sign is reversed for ease of visualization (i.e., the data suggest that speech is faster than song. The effect size is originally measured by relative effect, and that result is transformed into Cohen’s d for interpretability. The red shaded area surrounded by vertical lines at ±0.4 indicate the “smallest effect size of interest” (SESOI) suggested by Brysbaert (2019). See Fig. 2 for a schematic of how each effect size is calculated from each pair of sung/spoken recordings.

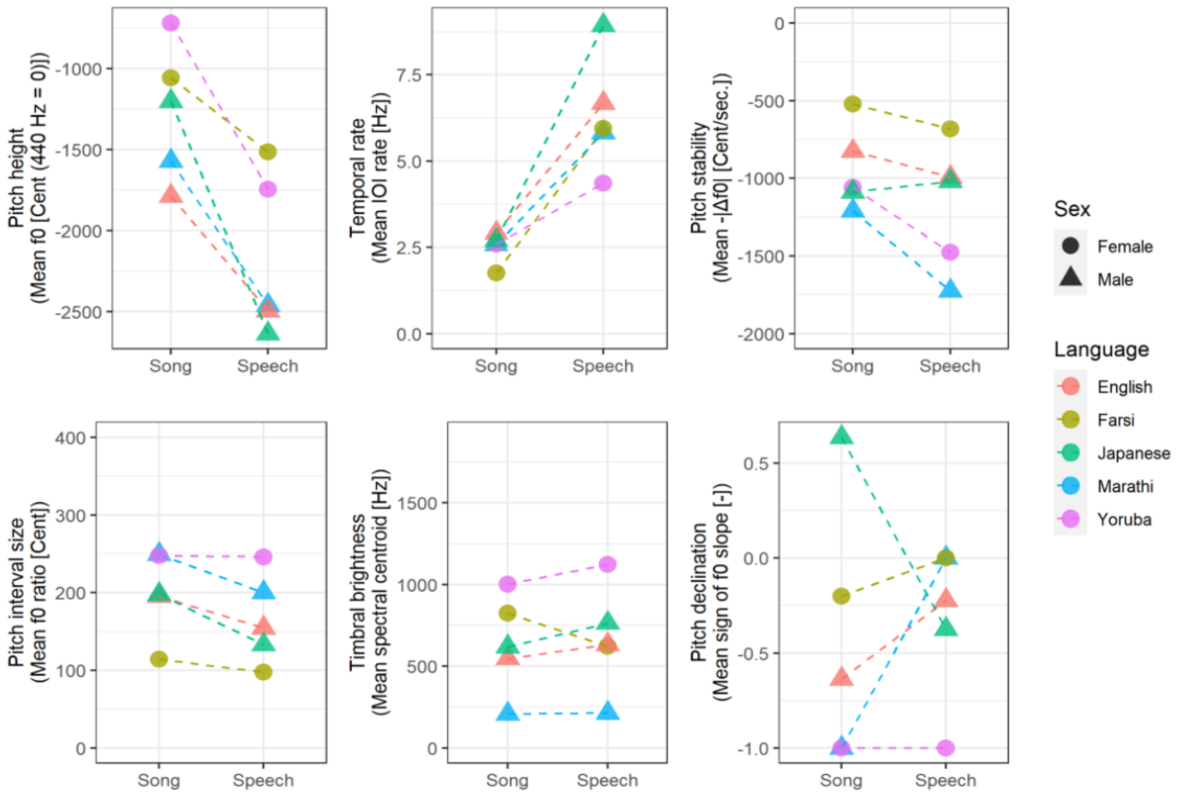


Figure S3. **Alternative visualization of Figure S2 showing mean values of each feature of song and speech, rather than paired differences.** "Speech" indicates spoken description (not lyric recitation). This figure allows us to visualize some trends not viewable from Figure S2, such as absolute values of each feature. For example, male voices all tend to be lower-pitched than female, but regardless of sex all singers use higher pitch for singing than speaking. (See Fig. S8 for an alternate version including exploratory analyses comparing instrumental and recited versions.)

In addition to the above main pilot analysis, we conducted two additional pilot analyses to validate our choice of duration of recording and annotation procedure. First, we investigated how estimated effect sizes vary with length of recording excerpt analyzed (Fig. S4). We concluded that 20 seconds approximately optimizes the tradeoff between accuracy of effect size estimation and the substantial time required to manually annotate onsets (roughly 10-40 minutes per 10 seconds of recording, with spoken description often taking several times longer to annotate than sung, instrumental, or recited versions).

Second, we had each of the five coauthors who annotated pilot data for their own language re-annotate a 10-second excerpt of their own recording (to determine intra-rater reliability) and then also annotate a 10-second excerpt of recordings in all other languages (to determine inter-rater reliability). They first did this once without any segmented text provided, and then corrected this after being provided with segmented texts. We then compared all these recordings against automated algorithms widely used in speech analysis (de Jong & Wempe, 2009; Mertens, 2022) to determine reliability of automated methods (Fig. S6).

The results of human-human comparisons were somewhat ambiguous, but overall suggested that (1) between-annotator differences in onset and break annotation are negligible even for different languages (provided they are provided with segmented texts),

(2) within-annotators randomness of annotation is also negligible as well, and (3) effect sizes based on the annotation provided by automated methods can be significantly different from human annotations. Note that Fig. S6 only compares temporal rate and pitch interval size, since most other features did not require manual annotations, while pitch declination was not analyzed because the 10-second excerpts were too short to have enough phrases to evaluate. Although our validation suggests the value of manual annotation, it would be desirable to increase its efficiency in future via options such as semi-automated methods or crowd-sourcing (though there will likely be tradeoffs between data quality and quantity; cf. Cychosz et al., 2021).

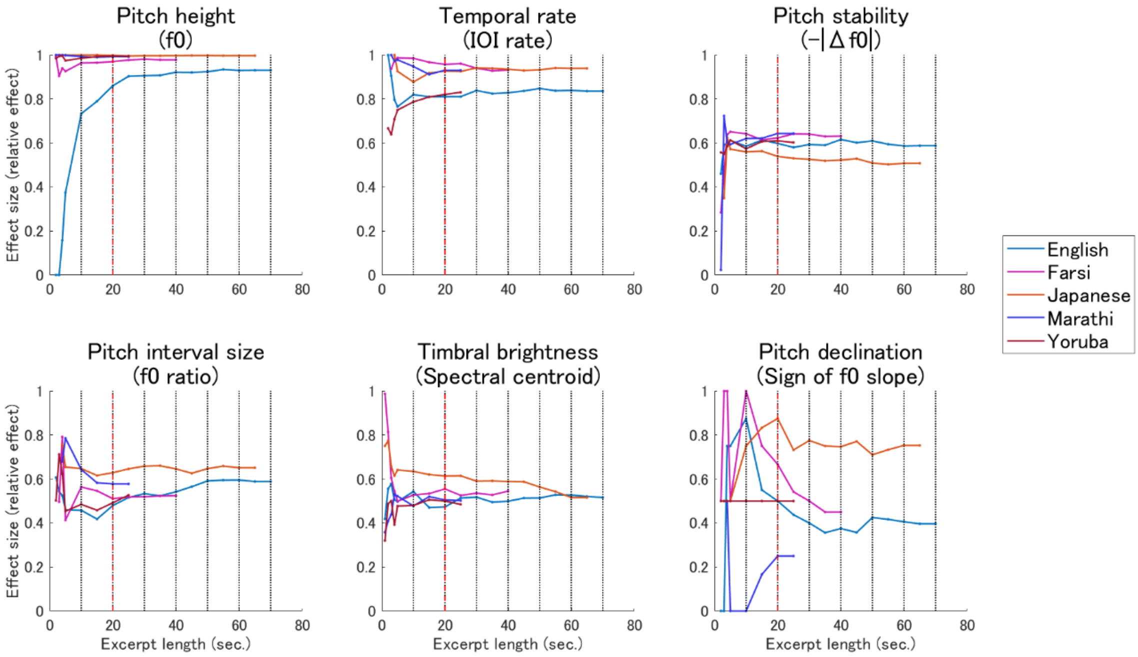


Figure S4. **Relationship between the duration of recording excerpt analyzed and estimated effect size for the 6 features and 5 sets of pilot recordings analyzed in Fig.S2.** Since the length of the pilot recordings ranged from under 30s to over 70s, plots are truncated at the point when there is no longer enough matching sung and spoken audio recording for that language (e.g., 25s for Marathi and Yoruba, 70s for English). The red vertical dashed line at 20s indicates the length we concluded approximately optimizes the tradeoff between accuracy of effect size estimation and the substantial time required to manually annotate onsets.

S1.5. Power analysis

We performed a power analysis to plan the number of recording sets (corresponding to the number of studies in meta-analysis) necessary to infer the statistical significance of the specified analyses. Because our pilot data consisting of only 5 recording sets is too small to empirically derive reliable effect size estimates, our power analyses used an SESOI corresponding to d = .4 (see Anvari & Lakens, 2021; Brysbaert, 2019 for the use of SESOI for sample size planning). However, there is one nuisance parameter in the model (i.e. between-study variance) necessary to specify for the power analysis, and we set this value with the estimate from the pilot data as a workaround.

Although we are planning to use the Benjamini-Hochberg step-up procedure (Benjamini & Hochberg, 1995) in our hypothesis testing, since the actual critical value depends on the p-value we will observe, it is challenging to specify sample size based on the false discovery rate especially when using nonparametric statistics, though some methods are available for parametric models (Jung, 2005; Pounds & Cheng, 2005). Therefore, we use the family-wise error rate for setting the alpha level for sample size planning as a proxy. Although it is known that when all null hypotheses are true, the false discovery rate becomes equal to the family-wise error rate (Benjamini & Hochberg, 1995), and the required sample size does not differ significantly between false discovery rate methods and stepwise family-wise error control methods in certain cases (Horn & Dunnett, 2004), our case may not necessarily match these conditions. Therefore our sample size estimate will be equal to or more than the size required for specified power assuming the alpha level determined by Bonferroni correction to set a stricter critical value.

We define the alpha level as 0.05 divided by six which is a family-wise error control by Bonferroni correction, and the statistical power as 0.95 for our sample size planning. Our statistical model is Gaussian random-effect models as explained in 1.2 Analysis plan.

Our power analysis estimated that n=60 recording sets is estimated as the minimum required sample size to achieve the above type I and type II error control levels when testing our six null hypotheses (see Supplementary Materials S3.2 for details). The features other than the sign of f_0 slope (i.e. f_0, IOI rate, rate of change of f_0, f_0 ratio, and spectral centroid) were estimated to have a relatively low between-study (recording set) variance, so the required number of recording sets computed for each feature is estimated to be lower than 10. However, as shown in Fig. S2, the sign of f_0 slope has a large between-study variance, and that resulted in 60 recording pairs being needed.

Please note that our power analysis does not take into account the specific languages used. While it would be ideal to have models that capture how languages (and other factors such as sex, age, etc.) influence the song-speech difference, we do not have enough empirical data or prior studies to build such models at this moment. Hence we simply treat each recording data without such factors, controlling for language family relationships separately in our robustness analyses. Future studies may be able to better incorporate such factors in a power analysis based on the data our study will provide.

S1.6. Robustness analyses

S1.6.1. Exclusion of data generated after knowing the hypotheses

One distinctive aspect of this study is that the authors ourselves generate the data for the analysis. Traditionally, personnel who provide data are blinded from the hypotheses to avoid biases where researchers (consciously or unconsciously) collect data to match their predictions. Here, we attempt to control for bias by withholding from analysis of audio data until we confirm the in-principle acceptance of this manuscript. We collect most recordings in a way that coauthors do not have access to each others' audio recordings until In Principle Acceptance (IPA) of this Registered Report, so that hypothesis formation and analysis methodology are specified a priori before accessing and analyzing the audio recordings. Still, some data are generated from the core team who planned and conducted the pilot analyses and thus already knew most hypotheses before we decided this issue needed to be controlled for. Data from these authors may possibly include some biases due to knowing the details of the study (e.g., we may have consciously or unconsciously sung higher or spoke lower than we normally would to match our prediction that song would use higher pitch than speech). Therefore, we will test the robustness of our confirmatory analysis results by re-running the same analyses after excluding recordings provided by coauthors who already knew the hypotheses when generating data. Our confirmatory analyses test the direction of effect sizes, so applying the same tests allows us to check if that holds with varying conditions. In case the results of this analysis and the original confirmatory analysis do not match, we will interpret our results as not robust (whether due to potential confirmation bias or to other sampling differences) and will thus not draw strong conclusions regarding our confirmatory hypotheses.

S1.6.2. Potential dependency caused by language family lineage

Another potential bias in our design is the unbalanced sample of languages due to our opportunistic sampling design. Related languages are more likely to share linguistic features due to common descent, and sometimes these features can co-evolve following lineage-specific processes so that the dependencies between the features are observable only in some families but absent in others (Dunn et al., 2011)[4]. Thus, it is possible that our sample of speakers/singers may not represent independent data points. While our study includes a much more diverse global sample of languages/songs than most previous studies, like them our sample is still biased towards Indo-European and other larger languages families, which might bias our analyses. To determine whether the choice of language varieties affects our confirmatory analyses, we will re-run the same confirmatory analyses using multi-level meta-analysis models (linear mixed-effects models; Sera et al., 2019) with each recording set nested in the language family. We will perform model comparison using the Akaike Information Criterion (AIC; Bozdogan, 1987) for the original random-effects model and the multi-level model. The model having the lower AIC explains the data better in terms of the maximum likelihood estimation and the number of parameters (Watanabe, 2018), although critical assessment of information criteria and model selection methods in light of domain knowledge is also important (Dell et al., 2000). If the choice of model technique qualitatively changes the results of our confirmatory hypothesis testing, we will conclude that our results depend on the assumption of the language dependency..

S1.7. Exploratory analysis to inform future research

We are interested in a number of different questions that we cannot include in our main confirmatory analyses due to issues such as statistical power and presence of background noise. However, we plan to explore questions such as the following through post-hoc exploratory analyses, which could then be used to inform confirmatory analyses in future research:

S1.7.1. More acoustic features: We will also explore other features in addition to the specified five features to investigate what aspects of song and speech are similar and different. Supplementary Figure S9 shows the analysis using additional features.

[4] There is also some potential that musical and linguistic features may be related, although past analyses of such relationships between musical features and linguistic lineages have found relatively weak correlations (Brown et al., 2014; Matsumae et al., 2021; Passmore et al., Under review).

S1.7.2. Relative differences between features: Our confirmatory analysis will formally test whether a given feature is different or similar between song and speech, but will not directly test whether some features are more or less good than others at distinguishing between song and speech across cultures. To explore this question, we will rank the magnitude of effect sizes to investigate the most differentiating features and most similar features among the pairs of song and speech.

S1.7.3. Music-language continuum: To investigate how music-language relationships vary beyond just song and spoken description, we will conduct similar analyses to our main analyses but adding in the other recording types shown in Fig. 1 made using instrumental music and recited song lyrics.

S1.7.4. Demographic factors: Most collaborators also volunteered optional demographic information (age and gender), which may affect song/speech acoustics. Indeed, Fig. S3 suggests that pitch height differences between males and females are even larger than differences between song and speech. We will explore such effects for all relevant features.

S1.7.5. Linguistic factors: We will also investigate whether typological linguistic features affect song-speech relationships (e.g., tonal vs. non-tonal languages; word orders such as Subject-Verb-Object vs. Subject-Object-Verb languages; “syllable-timed” vs. “stress-timed” languages and related measurements of rhythmic variability (nPVI; cf. Patel & Daniele, 2003), etc.

S1.7.6. Other factors: In future studies, we also aim to investigate additional factors that may shape global diversity in music/language beyond those we can currently analyze. Such factors include things such as:
-functional context (e.g., different musical genres, different speaking contexts)
-musical/linguistic experience (e.g., musical training, mono/multilingualism)
-neurobiological differences (e.g., comparing participants with/without aphasia or amusia)

S1.7.7. Reliability of annotation process: Each of Ozaki’s annotations will be based on segmented text provided by the coauthor who recorded it, and Ozaki’s annotations will be checked and corrected by the same coauthor, which should ensure high reliability and validity of the annotations. However, in order to objectively assess reliability, we will repeat the inter-rater reliability analyses shown in Fig. S6 on a subset of the full dataset annotated independently by Savage without access to Ozaki’s annotations. Like Fig. S6, these analyses will focus on comparing 10s excerpts of song and spoken descriptions, randomly selected from 10% of all recording sets (i.e., 8 out of the 81 coauthors, assuming no coauthors withdraw). Ozaki’s annotations corrected by the original recorder will be used as the “Reference” datapoint as in Fig. S6, and Savage’s annotations (also corrected by the original recorder) will correspond to the “Another annotator” datapoints in Fig. S6. Note however that we predict that Savage’s corrected annotations will be more analogous to the “Reannotation” data points in Fig. S6, since in a sense our method of involving the original annotator in checking/correcting annotations is analogous to them reannotating themselves in the pilot study.

S1.7.8. Exploring recording representativeness and automated scalability: Because our opportunistic sample of coauthors and their subjectively selected “traditional” songs are not necessarily representative of other speakers of their languages, we will replicate our analyses with Hilton, Moser et al.’s (2022) existing dataset, focusing on the subset of languages that can be directly compared. This subset of languages will consist of 5 languages (English, Spanish, Mandarin, Kannada, Polish) represented by matched adult-directed song and speech recordings by ~240 participants (cf. Hilton et al. Table 1).

Because our main analysis method requires time-intensive manual or semi-manual annotation involving the recorded individual that will not be feasible to apply to Hilton et al.'s dataset, we will instead rely for our reanalysis of Hilton et al.'s data on purely automated features. We will then re-analyze our own data using these same purely automated features. This will allow us to explore both the scalability of our own time-intensive method using automated methods, and directly compare the results from our own dataset and Hilton et al.'s using identical methods.

Fig. S10 demonstrate this comparison using pilot data for one feature (pitch height) based on a subset of Hilton et al.'s data that we previously manually annotated (Ozaki et al., 2022), allowing us to simultaneously compare differences in our sample vs. Hilton et al.'s sample and automated vs. semi-automated methods. Even though this analysis focuses on a feature expected to be one of the least susceptible to recording noise (pitch height), our pilot analyses found that these were mildly sensitive to background noise, such that purely automated analyses resulted in systematic underestimates of the true effect size as measured by higher-quality semi-automated methods (Fig. S10). While our recording protocol (Appendix 2) ensures minimal background noise, Hilton et al.'s field recordings were made to study infant-directed vocalizations and often contain background noises of crying babies as well as other sounds (e.g., automobile/animal sounds; cf. Fig. S11), which may mask potential differences and make them not necessarily directly comparable with our results. This supports the need to compare our results with Hilton et al.'s using both fully-automated and semi-automated extracted features to isolate differences that may be due to sample representativeness and differences that may be due to the use of automated vs. semi-automated methods.

S2. Supplementary discussion of hypotheses and potential mechanisms

This section outlines the literature review on the comparative analyses of music and language, with special emphasis on relevant hypotheses regarding their evolutionary origins. This section introduces possible mechanisms underlying differences and similarities between song and speech. We have include this text here for completeness but placed it in the Suplementary Material rather than in the "Study aims and hypotheses" section of the main text because, while relevant to our hypotheses, most are not directly testable in our proposed design.

S2.1. Hypotheses for speech-song differences

We predict that the most distinguishing features will be those repeatedly reported in past studies, namely pitch height and temporal rate of sound production (Chang et al., 2022; Ding et al., 2017; Hansen et al., 2020; Merrill & Larrouy-Maestri, 2017; Sharma et al., 2021). Why have these features emerged specific to singing? From the viewpoint of the social bonding hypothesis, slower production rate may help multiple singers synchronize, facilitating "formation, strengthening, and maintenance of affiliative connections" (Savage et al., 2021). The social bonding hypothesis does not directly account for the use of high pitched voice; instead we speculate that this is related to the loudness perception of human auditory systems. It is known that the loudness sensitivity of human ears increases almost monotonically until 5k Hz. Furthermore, the magnitude of neural response to the frequency change by means of mismatch negativity also increases as the frequency range goes high in the range of 250 - 4000 Hz (Novitski et al., 2004). Therefore, heightening f_0 can be considered as conveying pitch information at a higher sensitive channel as possible. Also, in song and speech, melody is predominantly perceived via f_0, while timbre is predominantly perceived via the upper harmonics (Patel, 2008). Thus the tendency for music to emphasize melodic information and language to emphasize timbral information (Patel, 2008) may also explain a preference for higher sung pitch to optimize the frequency of the key melodic information. However, in adition to perceptual factors, higher pitch in singing may also be a consequence of the production mechanism required for the sustaining the pitched voice, especially when keeping sub-glottal pressure at a high level to sustain phonation, which may facilitate raising pitch (Alipour & Scherer, 2007).

Interestingly, higher pitch and longer duration are identified as features contributing to saliency and perceived emotional intensity of sounds (but also other factors such as greater amplitude and higher spectral centroid, see Anikin (2020) for a more comprehensive list). This suggests our features predicted to show differences may originate in non-verbal emotional expression. In addition, the pattern of higher pitch height and slower sound production rate is also cross-culturally characteristic of infant-directed speech compared to adult-directed speech (Cox et al., 2022; Hilton et al., 2022). Along with other features in infant-directed speech, this difference is argued to play an important role in linguistic and social development (Cox et al., 2022).

Pitch discreteness is often considered a key feature of music (Brown and Jordiana, 2013; Fitch, 2006; Haiduk & Fitch, 2022; Savage et al., 2015; Ozaki et al., 2022; Vanden Bosch der Nederlanden et al., 2022). However, to our knowledge, there is no well-established way to analyze this property directly from acoustic signals. In this study, we measure pitch stability as a proxy of pitch discreteness. Our pitch stability measures how fast f_0 modulates, although we admit this may not fully account for the characteristics of pitch discreteness. For example, recent studies indicated pitch discreteness might relate to the ease of memorization (Haiduk et al., 2020; Verhoef & Ravignani, 2021), but our measurement does not directly take into account such effects. Based on the pilot analysis (Fig. S2), we confirmed that pitch stability can demonstrate the expected trend (i.e. more stable pitch in singing). The effect size can be medium (size corresponding to Cohen's d of 0.5) at best, but considering the limited capacity of human pitch control in singing (e.g. imprecise singing; Pfordresher et al. (2010)), it is plausible that pitch stability may not matter for the distinction between song and speech as much as pitch height and temporal rate. Still, we predict this feature is worth testing for cross-cultural differences between song and speech, particularly given its prominence in previous debate (including Lomax an Grauer's definition of song cited in the introduction). In fact, several empirical studies documented that song usually produces more controlled f_0 than speech (Natke et al., 2003; Raposo de Medeiros et al., 2021; Stegemöller et al., 2008; Thompson, 2014).

In relation to the differentiation between song and speech, Ma et al. (2019) provided an intriguing simulation result of how a single vocal communication can diverge into a music-like signal and speech-like signal through transmission chain experiments. Their experiment was designed to test the musical protolanguage hypothesis (Brown, 2000) and found that music-like vocalization emerges when emotional functionality is weighted in the transmission and speech-like vocalization emerges when referential functionality is necessitated. This result may imply a scenario that singing behaviour emerged as one particular form of emotional vocal signals conveying internal states of the vocalizer, though its evolutionary theory has not particularly targeted music (Bryant, 2021). In fact, a melodic character of music is often considered to function in communicating mental states (Leongómez et al., 2022; Mehr et al., 2021) and infant-directed singing acts as the indication of emotional engagement (Trehub et al., 1997). Since our recordings are solo vocalizations however, our recordings may not display key features facilitating synchronization of multiple people such as regular and simple rhythmic patterns. Although this is out of scope of our study, it is intriguing to investigate whether this speculation also holds in the case of solo music traditions (Nikolsky et al., 2020; Patel & von Rueden, 2021).

S2.2. Hypotheses for speech-song similarities

We predict pitch interval size, timbre brightness and pitch declination will not show marked differences between song and speech. Amongst these three features, we introduce a novel way for assessingpitch interval size. Although there is a line of research studying musical intervals based on the limited notion of the interval defined with the Western twelve-tone equal-tempered scale (Ross et al., 2007; Schwartz et al., 2003; Stegemöller et al., 2008; but cf. Han et al., 2011; Robledo et al., 2016), our study treats interval more generally as a ratio of frequencies to characterize the interval of song and speech in a unified way.

Stone et al. (1999) reported that country singers use similar formant frequencies in both song and speech which is consistent with our pilot analysis (Figure S2), and they argued that the use of higher formant frequencies (e.g. singer's formant, see also Lindblom & Sundberg (2007)) in Western classical music tradition stemmed from the necessity of the singer's voice to be heard over a loud orchestral accompaniment. Similarly, Stegemöller et al. (2008) confirmed that speech and song have a similar spectral structure. Although we can find studies showing higher brightness in singing performed by professional singers (Barnes et al., 2004; Merrill & Larrouy-Maestri, 2017; Sharma et al., 2021; Sundberg, 2001), our dataset does not necessarily consist of recordings by professional musicians and as in the case of Stone et al. (1999) the prominent use of the high formant frequencies in singing may depend on musical style (but see Nikolsky et al., (2020) for the role of timbre played in personal music tradition). However, we would like to note that other aspects of timbre such as noisiness (spectral flatness) can potentially indicate the difference between song and speech (Durojaye et al., 2021).

Cross-species comparative studies identified that the shape of pitch contour is regulated by the voice production mechanism (Tierney et al., 2011; Savage et al., 2017). Since both humans and birds use respiratory air pressure to drive sound-producing oscillations in membranous tissues (Tierney et al., 2011), their pitch contours tend to result in descending towards the end of the phrase. Although previous studies only compared on pitch contours of human music (instrumental and vocal) and animal song, we predict the same pattern can be found in human speech since it still relies on the same motor mechanism of vocal production. More precisely, pitch declination is predicted to happen when subglottal pressure during exhalation can influence the speed of vocal fold vibration; the high pressure facilitates faster vocal fold vibration, and low pressure therefore makes the vibration relatively slower. Declarative speech is also subject to this mechanism (Ladd, 1984; Slifka, 2006).

S3. Features

The six features introduced in the main section are extracted as follows:

S3.1. Pitch height (f_0): f_0 is estimated in a semi-automated way like the annotation in the Erkomaishvili dataset (Rosenzweig et al., 2020), which used an interactive f_0 extraction tool (Müller et al., 2017). We created a graphical user interface application with the following extraction process: 1) create the time-frequency representation of the audio signal using the fractional superlet transform (Bârzan et al., 2021; Moca et al., 2021); 2) a user specifies the set of points (beginning, end, upper and lower bound of frequency, and optional intermediate point(s) to be included in the contour) on the time-frequency plane to constraint the search region of f_0; 3) estimate an f_0 contour using the Viterbi algorithm (Djurović & Stanković, 2004). It is also possible to manually draw/delete/modify the contour if the f_0 is deemed not reliably estimated automatically due to severe interference by noise. The frequency resolution is 10 cents with 440 Hz = 0 (octave is 1200 cents), and the time resolution is 5 ms.

S3.2. Temporal rate (Inter-onset interval [IOI] rate): Inter-onset interval rate is measured by first taking the difference between adjacent onset annotation times or onset and break annotation times and then taking that reciprocal. Our proxy for temporal rate is the inter-onset interval of consecutive P-centers (perceptual centers; Danielsen et al., 2019; Howell, 1988; Morton et al., 1976; Pompino-Marschall, 1989; Scott, 1998; Vos & Rasch, 1981), which is approximately similar to but not identical to the rate of linguistic and musical acoustic units (e.g. syllables, notes). Onset is a perceptual center determined by the person who made the recording.

S3.3. Pitch stability ($-|\Delta f_0|$): The rate of change of f_0 is the negative absolute value of the numerical differentiation at each sampling point of the f_0 contour. The negative sign is used so that higher values indicate greater pitch stability. We use Shao & Ma's (2003) wavelet method with a first-order derivative of Gaussian to derive this because it is robust to noisy f_0 contours such as the ones in our pilot dat. We use 20 ms as the standard deviation parameter of the first-order derivative of Gaussian to smooth the noise, which corresponds to the scaling factor of the wavelet function.

S3.4. Pitch interval size: Pitch interval is usually expressed as the ratio of pitch of two notes. We generalize this concept as follows. Firstly, segment an f_0 contour with the onset and break times. Secondly, take the outer product of the antecedent segmented f_0 contour and the reciprocal of the consequent f_0 contour. Here, rather than estimating a single representative pitch from each segment, we take exhaustive combinations of the ratio of f_0 values between adjacent segments and evaluate the interval as a distribution. This approach allows us to quantify intervals on both musical and linguistic acoustic signals. We calculate this outer product from each pair of adjacent segmented f_0 contours and aggregate all results as the pitch interval of the recording. However, one drawback of this method is the number of data points tends to become large due to taking outer products, though it can be mitigated by lengthening the sampling interval of f_0. Figure S5 shows a schematic overview of our approach.

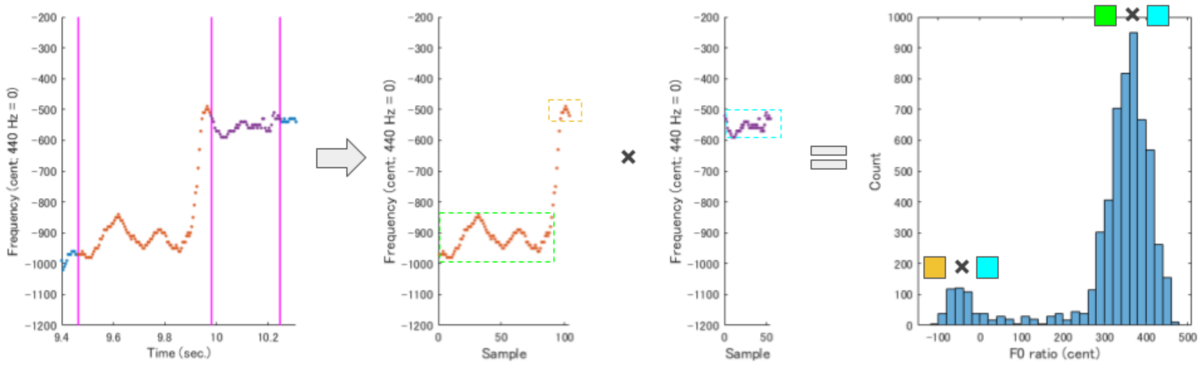


Figure S5. Process of computing f_0 ratios. The leftmost figure shows an f_0 contour which is segmented by three onset times. Then, the pitch ratio of the antecedent segmented f_0 contour (orange) and the consequent f_0 contour (purple) is calculated by taking exhaustive pairs of samples from two signals (104 samples × 55 samples in this example). The rightmost figure shows the obtained intervals by histogram which displays two peaks. The right-hand mode is the interval of ascending direction (around 370 cents) generated from the green rectangle part. The left-hand mode is the interval of descending direction (around -50 cents) generated from the orange rectangle part. Note that this example uses the cent scale rather than the frequency scale so that intervals can be calculated by subtraction.

S3.5. Timbral brightness (spectral centroid): Spectral centroid is computed by obtaining a power spectrogram using 0.032 seconds Hanning window with 0.010 seconds hop size. The original sampling frequency of the signal is preserved. Please note silent segments during breathing/breaks are also included. However, the majority of the recordings contain a voice (or instrument), so the influence from silent segments should be minimal. Although we tried using an unsupervised voice activity detection algorithm by Tan et al. (2020), it was challenging to assess how much the failure of detection can impact the measurement of the effect size. The unsupervised algorithm was chosen to avoid the assumption of particular languages and domains as possible since we deal with a wide range of language varieties and audio signals of both music and language domains, which is usually beyond the scope of voice activity detection algorithms in general. Another limitation is that the measurement of spectral centroid can be affected by noise due to poor recording environment or equipment. However, our study focuses on the difference in terms of the relative effect in spectral centroid in two recordings (expected to be recorded in the same environment/equipment/etc.), and we confirmed that the difference in spectral centroid itself is not markedly influenced by noise if the two recordings are affected by the same noise.

S3.6. Pitch declination (Sign of f_0 slope): Pitch declination is estimated in the following steps. First, a phrase segment is identified by the onset annotation after the break annotation (or the initial onset annotation for the first phrase) and the first break annotation following that. Secondly, an f_0 contour is extracted from that segment. We treat f_0s as response variable data and correspondence times as dependent variable data. If there are frames where f_0 is not estimated, we discard that region. Finally, we fit a linear regression model with Huber loss and obtain the slope. If the pitch contour tends to have a descending trend at the end of the phrase, we expect the slope of the linear regression tends to be negative. MATLAB's fitlm() function was used to estimate the slope. Figure 3 illustrates linear models fitted to each phrase.

S4 Statistical models and power analysis

S4.1 Statistical models

The Gaussian random-effects model used in meta-analysis is (Brockwell & Gordon, 2001; Liu et al., 2018)

$$Y_i|\theta_i \sim \mathcal{N}(\theta_i, \sigma_i^2),\ \theta_i \sim \mathcal{N}(\mu_0, \tau^2),\ i = 1, \ldots, K$$

Y_i is the effect size (or summary statistics) from ith study, θ_i is the study-specific population effect size, σ_i^2 is the variance of ith effect size estimate (e.g. standard error of estimate) which is also called the within-study variance, μ_0 is the population effect size, τ^2 is the between-study variance, and K is the number of studies. In our study, Y_i is the relative effect and σ_i^2 is its variance estimator (Brunner et al., 2018). In addition, the term "studies" usually used in meta-analysis corresponds to recording sets. This model can also be written as

$$Y_i \sim N(\mu_0, \sigma_i^2 + \tau^2),\ i = 1, \ldots, K$$

S4.2 Power analysis

We first describe the procedure for sample size planning for the hypotheses testing differences (H1-3). In this case, hypothesis testing evaluates $H : \mu_0 = \mu_{\text{null}}$ vs. $K : \mu_0 > \mu_{\text{null}}$, which means that the null hypothesis assumes the population effect size is the same as no difference and the alternative hypothesis assumes the difference exists in the positive direction (one-sided). Since we use relative effects as our effect sizes, we define $\mu_{\text{null}} = 0.5$. As described in "S1.5 Power Analysis", we decided to use SESOI for sample size planning, meaning we assume that the population effect size is the same as SESOI. Therefore, we specify where $\mu_0 = \Phi(0.4/\sqrt{2}) \approx 0.6114$ $\Phi(\cdot)$ is the standard cumulative normal distribution.

The power of the Gaussian random-effects model is given by (Hedges & Pigott, 2001; Jackson & Turner, 2017)

$$\beta(\delta, \tau^2, \boldsymbol{\sigma}) = 1 + \Phi(-Z_\alpha - \delta/\sqrt{V_R}) - \Phi(Z_\alpha - \delta/\sqrt{V_R}) \tag{1}$$
$$V_R = \frac{1}{\sum_{i=1}^{K}(\sigma_i^2 + \tau^2)^{-1}}$$

, where Z_α satisfies $\Phi(Z_\alpha) = \alpha$ that α is the significance level of the test, and δ is non-centrality parameter defined as $\delta = \mu_0 - \mu_{\text{null}}$ which represents the gap between the parameter of the null hypothesis model and the population parameter.

In order to perform the power analysis, we first need to specify the nuisance parameter τ^2 (between-study variance) which is generally unknown. We use DerSimonian-Laird estimator (Dersimonian & Laird, 1986; Liu et al., 2018) to estimate τ^2 using pilot data. However, there is the issue that the within-study variance σ_i^2 of sign of f_0 slope of the Yoruba recordings became 0. This happened because the signs of f_0 slope of singing and spoken description are all -1, which means f_0 contours of all phrases show better fitting to a downward direction than the upward. Zero variance causes divergence (i.e., +∞) in the weighting used in the

DerSimonian-Laird estimator. As a workaround, the hypothetical standard error of the relative effect is estimated by assuming at least one of the observations was +1 (i.e. one of the f_0 slopes fits the upward direction). Specifically, we first re-estimated the standard error of the relative effect with both patterns that one of the signs is +1 in either the singing or spoken description. Then we took the smaller variance estimate for the hypothetical standard error of this recording set.

Furthermore, we also need assumption for σ_i^2 to calculate the power and to estimate the necessary number of studies K since the power is the function of the non-centrality parameter, between-study variance, and within-study variances. We assume the within-study variance has a mean and plug in the average of the within-study variances from pilot data. Algorithmically, our procedure is

1. Estimate τ^2 and $\delta = \mu_0 - \mu_{\text{null}}$.
2. Calculate the average of the within study variance.

$$\bar{\sigma}^2 = \frac{1}{N}\sum_{n=1}^{N}\sigma_n^2$$

   N is the number of pilot recording sets (i.e. N = 5) here.
3. Set $\boldsymbol{\sigma} = \{\sigma_1, \ldots, \sigma_N\}$
4. Calculate the power using the equation (1)
5. If the calculated power is lower than the target power then,
   $\boldsymbol{\sigma} \leftarrow [\boldsymbol{\sigma}\ \ \bar{\sigma}]$ (append $\bar{\sigma}$ to the current $\boldsymbol{\sigma}$) and return to 4.
   Otherwise, take the number of elements of $\boldsymbol{\sigma}$ as the necessary number of studies.

For the power analysis of equivalence tests (H4-6), we first note that the Gaussian random-effects model is equivalent to a normal distribution since random-effects models are Gaussian mixture models having the same mean parameter among components, therefore

$$\begin{aligned} p(\mathbf{Y}|\boldsymbol{\sigma}, \tau^2, \mu_0) &= \frac{1}{K}\sum_{i=1}^{K}\mathcal{N}(Y_i|\mu_0, \sigma_i^2 + \tau^2) \\ &= \mathcal{N}(Y_i|\mu_0, \sigma_\tau^2),\ i = 1 \ldots K \end{aligned}$$

where

$$\sigma_\tau^2 = \frac{1}{K}\sum_{i=1}^{K}(\sigma_i^2 + \tau^2)$$

We use this reparameterized version for equivalence tests. We estimate the necessary number of studies K by simulating how many times the test can reject a null hypothesis under the alternative hypothesis being true out of the total number of tests. Specifically, the rejection criteria is (Romano, 2005)

$$K^{1/2}|\bar{Y}_K| \leq C(\alpha, \delta, \sigma_\tau)$$

where $C = C(\alpha, \delta, \sigma)$ satisfies

$$\Phi\left(\frac{C-\delta}{\sigma}\right)-\Phi\left(\frac{-C-\delta}{\sigma}\right)=\alpha$$

$\bar{Y}_K$ is sample estimate of the mean, and we use the estimated μ_0 instead of the simple average of effect sizes. Here, δ defines the boundary for equivalence testing, namely $H:|\theta|\geq\delta \text{ vs. } K:|\theta|<\delta$ that the boundary is symmetric at 0. We set the boundary parameter based on SESOI $\delta=\Psi(0.4/\sqrt{2})-0.5\approx 0.1114$ that shifts the center of the relative effect to 0 from 0.5, and specify $\theta=0$ assuming that the population effect sizes of the features to be tested are null. When running the simulation, we draw random samples as $Y_i\sim\mathcal{N}(\mu_0,\sigma_\tau^2)$ and increase the number of studies K gradually until the simulation satisfies the expected power under the specified significance level.

S5 Supplementary Figures

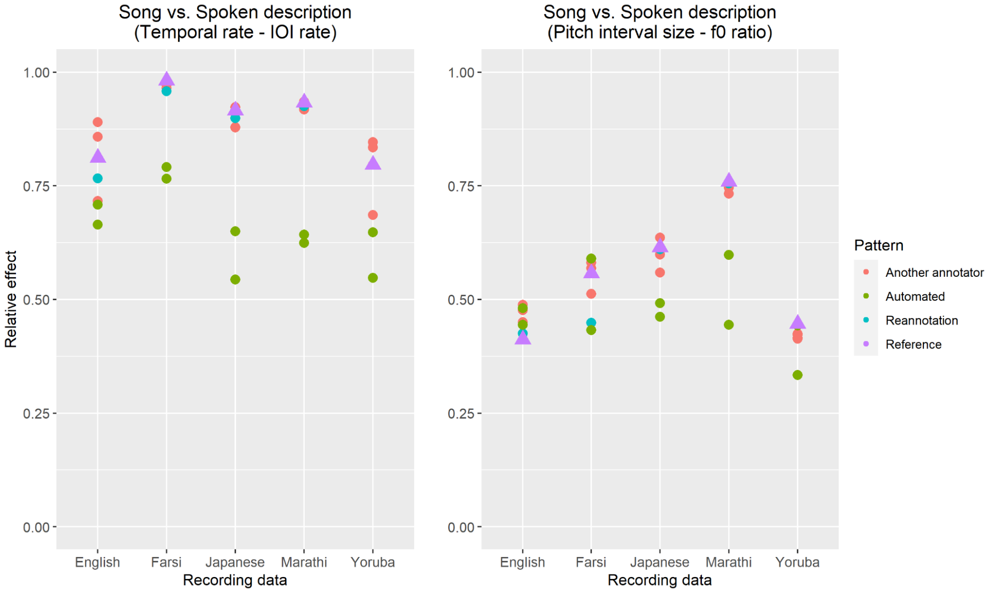


Figure S6. Within- and between-annotators randomness of onset annotations including automated methods (de Jong & Wempe, 2009; Mertens, 2022) discussed in Section S1.4 “Pilot data analysis”. 10-second excerpts were used. Reference is the result of the annotation by the person who originally made the recording.

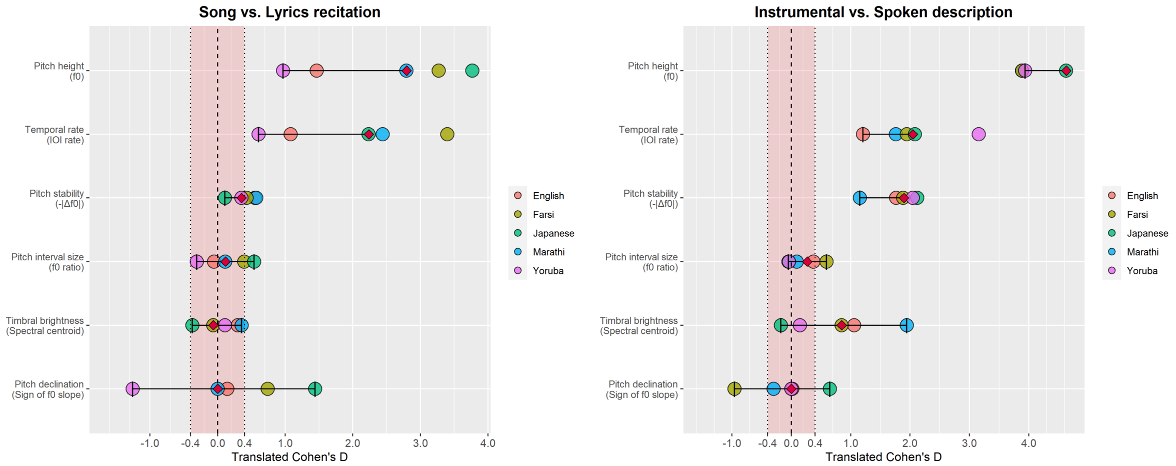


Figure S7. Effect sizes of each feature across five languages using the pilot data as in Figure S2 but with exploratory comparisons with recitation and instrumental recording types.

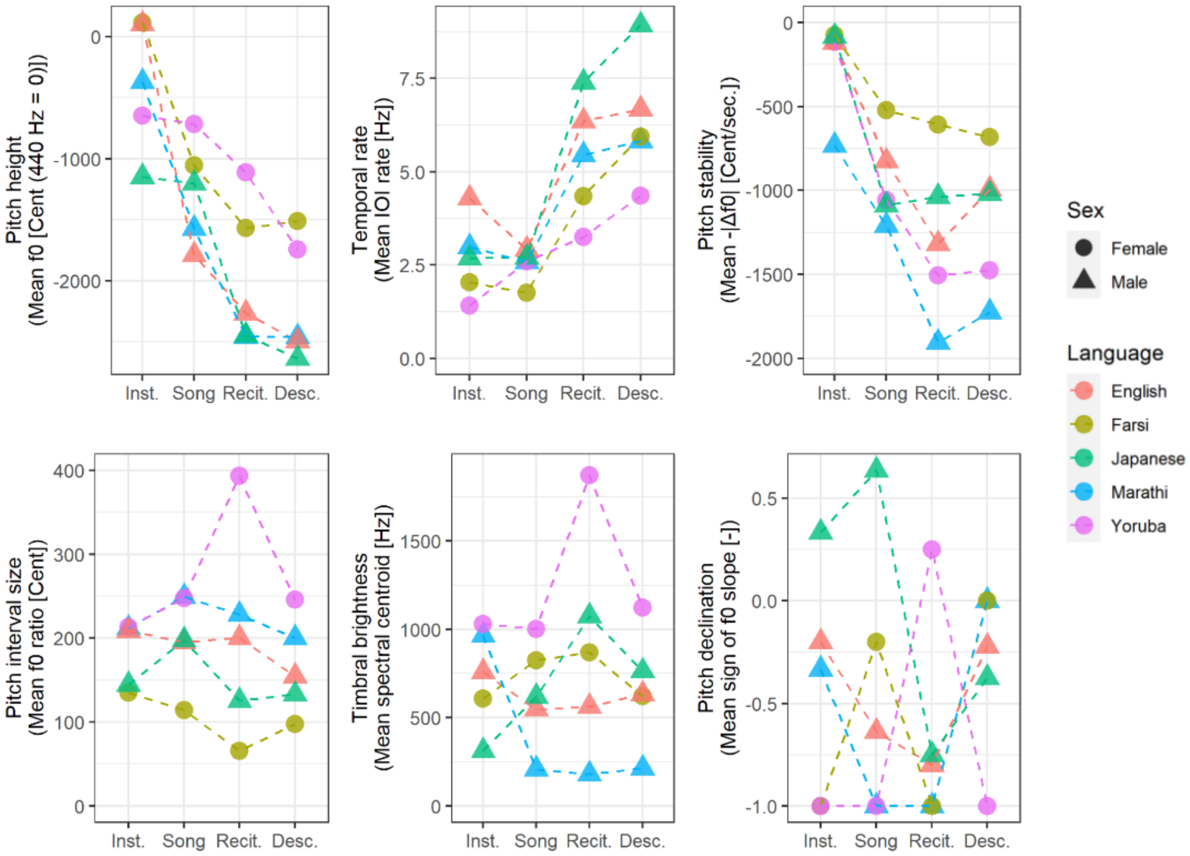


Figure S8. Mean values of each feature as in Figure S3 but with all recording types (including recitation and instrumental). “Desc.” means spoken description, “Recit.” means recited lyrics.

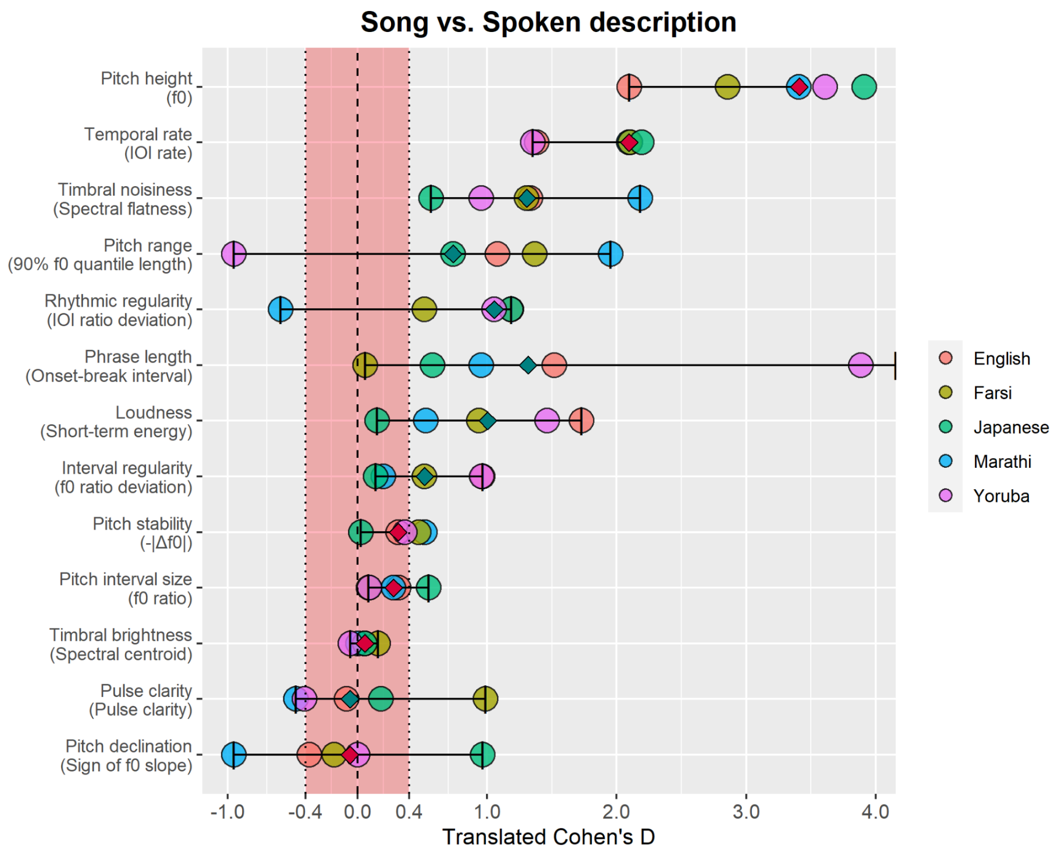


Figure S9. Effect sizes of each feature across five languages using the pilot data as in Figure S2 with additional exploratory features. Green-colored diamonds and two-sided confidence intervals are used for the features that hypotheses are not specified.

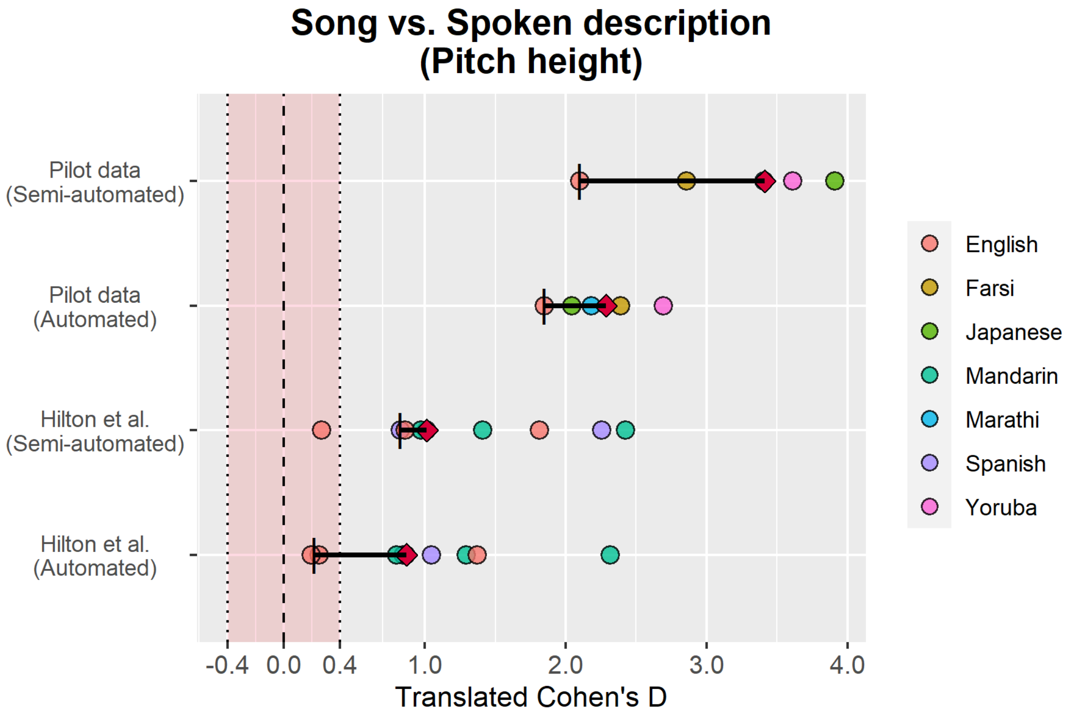


Figure S10. Pilot analysis of a subset of Hilton et al.'s (2022) data (pairs of adult-directed singing/speaking recordings from n=9 participants speaking English, Spanish, or Mandarin) focusing on pitch height. Ozaki et al., (2022) previously analyzed this subset for preliminary analyses using the same method described in S2.1 to avoid contamination by various noises included in audio (vocalization by babies, car noises, etc.), which allows us to explore issues such as whether such extraneous noises are likely to be a concern in our planned fully automated analysis of Hilton et al.'s full dataset (cf. Fig. S11). Although all four conditions demonstrate the predicted trend of song being consistently higher than speech, the effect size varies depending on the dataset and analysis method used (see Section S1.7.8. for discussion).

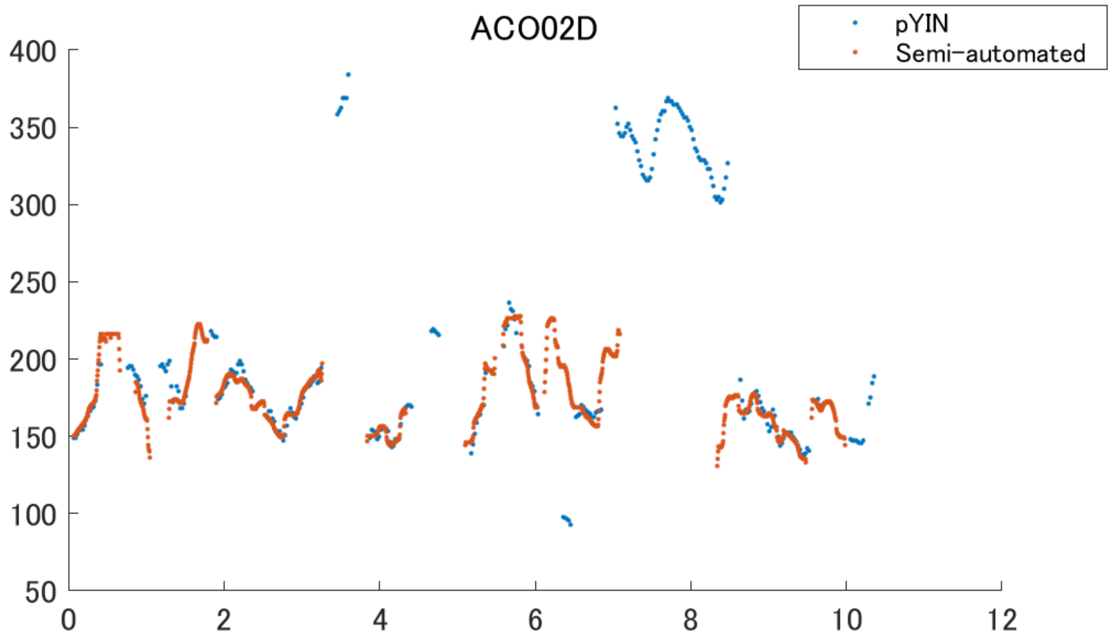


Figure S11. An example of fully-automated vs. semi-automated f0 extraction underlying the analyses in Fig. S7 for one of the field recordings from Hilton et al.'s dataset. AC002D = adult-directed speech [D] from individual #02 from the Spanish-speaking Afro-Colombian [ACO] sample). While the extracted f0 values are generally similar, the fully automated pYIN method sometimes has large leaps, particularly when there are external noises and the main recorded individual stops vocalizing to breathe (here the high-pitched blue contours at around 3.5 and 8 seconds correspond to the vocalizations of a nearby child while the recorded adult male takes a breath).

S6 Exploratory features.

The summary of the additional features that will be examined in the exploratory analysis is as follows.

7) Rhythmic regularity (IOI ratio (Roeske et al., 2020) deviation) [*dimensionless*],
    - Absolute difference between the observed IOI ratios and the nearest mode estimated from the observed IOI ratios. If the perceived onsets constitute similar ratios over the recording, each data point (IOI ratio) would be concentrated around the mode thus small deviation from the most typical ratio would be expected. This idea is similar to measuring the variance of the within-cluster that modal clustering is used to create clusters. However, the deviation of each data point from a cluster centroid is measured instead of variance.

- Various methods for density modes (equivalently zero-dimensional density ridges or degree zero homological features) have been recently proposed (Chacón, 2020; Chaudhuri & Marron, 1999; Chazal et al., 2018; Chen et al., 2016; Comaniciu & Meer, 2002; Fasy et al., 2014; Genovese et al., 2014; Genovese et al., 2016; Sommerfeld et al., 2017; Zhang & Ghanem, 2021). Here, we adopted techniques of topological data analysis. In particular, we use the mean-shift algorithm (Comaniciu & Meer, 2002) to detect the modes. Gaussian kernels are used and we choose to obtain a bandwidth parameter using Pokorny et al. (2012)'s method that selects a bandwidth from the range that the Betti number (number of modes in this case) is most stable (Carlsson, 2009; Pokorny et al., 2012). Note that this is not the only way and other criteria also exist (e.g. Genovese et al., 2016; Chazal et al., 2018) for the bandwidth selection from the viewpoint of topological features. The search space of bandwidth is set as $\sigma\{\log(n)/n\}$ as minimum following Genovese et al. (2016). The maximum bandwidth value is set as Silverman's rule-of-thumb (Silverman, 1986) since this bandwidth selection is usually considered oversmoothing (Hall et al., 1991), and this idea was previously also used for ridge detection analysis (Chen et al., 2015). Removing low density data points (outliers) to infer the persistent homology features is recommended (Chazal et al., 2018), so we set the threshold to eliminate data points that is $\{X_i : \hat{p}(X_i) < t\},\ t = \max(2, 0.01N)K(X;h)$ where $K(X;h)$ is a kernel density function with the bandwidth parameter h and $\hat{p}(X)$ is kernel density estimate using all data points. This threshold removes samples from density created by a few samples; equivalent to density less than 2 data points or less than 1% of the number of data points. Figure S12 illustrates our approach.

8) Phrase length (duration between two breaths/breaks) (onset-break interval) [*seconds*],
    - An interval between the first onset time after a break time (or the beginning onset time) and the first break time after the onset time, roughly corresponding to the length of a musical phrase or spoken utterance..
9) Pitch interval regularity (f_0 ratio deviation) [*cent*],
    - Like the IOI ratio deviation, the absolute difference between the observed f_0 ratios and the nearest mode. The method for calculating this feature is identical to the IOI ratio deviation, but for frequency rather than for time..
10) Pitch range (phrase-wise 90% f_0 quantile length) [*cent*],
    - The phrase is an interval as defined in 8) Phrase length. The sample quantile length of f_0 within each phrase is extracted.
11) Intensity (short–term energy) [*dimensionless*],
    - We measure the energy of the acoustic signal as a rough proxy of loudness although loudness is a perceptual phenomenon and these two are not necessarily equal. The short-term energy is the average of the power of the signal within a rectangular window whose length is 25 ms. We slide this window every 12.5 ms to collect the short-term energies of the recording. In order to avoid including the unvoiced segments, the energy is calculated from the samples within IOIs or onset-break intervals. Since the relative effect is invariant with the order-preserving transformation, we do not apply a

logarithm though the feature name is intensity. There are some limitations in this feature. One limitation is that recording is not strictly controlled. However, assuming the collaborator follows the protocol (e.g. keep the same distance between microphone and mouth/instrument and use the same recording device and recording environment across recordings), we assume the intensityof the recordings within each collaborator can be roughly compared. Another limitation is that the recording method is not unified across the collaborators. Therefore, even if there are the same level of differences in sound pressure level of singing and speech among the collaborators, the effect sizes to be calculated can be different. More precise control of recording conditions would be necessary for more accurate measurement of the difference in loudness in the future study.

12) Pulse clarity [*dimensionless*],
    - Pulse clarity is calculated using MIRToolbox V1.8.1 (Lartillot et al., 2008).
13) Timbre noisiness (spectral flatness (Johnston, 1988; Peeters, 2004)) [*dimensionless*]
    - Spectral flatness is measured at each acoustic unit, namely inter-onset intervals and onset-break intervals, as in Durojaye et al. (2021).

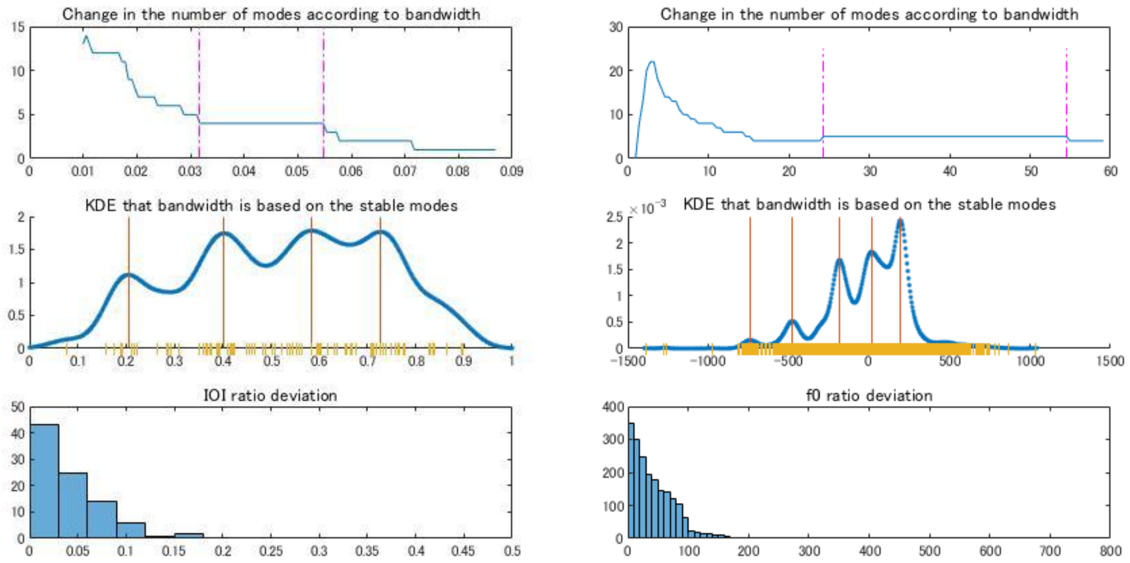


Figure S12. Illustration of the computation of IOI ratio deviation and f_0 ratio deviation. The interval between the magenta lines is the range of the bandwidth parameter that Betti number (number of modes) is most stable which we interpret as indicating the strong persistence of the topological features. Note that due to the removal of data points from the low density region, the number of modes does not simply monotonically decrease with the increase in the bandwidth parameter.

S7. Manipulation of features to demonstrate our designated SESOI (Cohen's D = 0.4).

Following Brysbaert's (2019) recommendation, we use the relative effect corresponding to 0.4 of Cohen's D as the SESOI for our hypothesis testing. Although the choice of 0.4 of Cohen's D is somewhat arbitrary, we empirically measured how much such differences correspond to the physical attribute of audio using our pilot data focusing on pitch height and temporal rate. For each pair of singing and spoken description recording, we first measured the relative effect (3rd column: Relative effect (p_{re})). Then, we manipulated the corresponding feature of the song to result in a relative effect equal to 0.61 (corresponding to 0.4 of Cohen's D) and 0.5 (corresponding to no difference, 0.0 of Cohen's D). Specifically, we shifted down the entire f_0 for pitch height and slowed down the playback speed for temporal rate. The 4th and 5th columns show actual scale factors identified at each recording and feature. For example, the first row indicates the f_0 of the sung version needed to be shifted 730 cents downward to manipulate the difference in this feature between singing and spoken description to be as small as our proposed SESOI of Cohen's D = .4. Similarly, the sixth row indicates the IOIs of singing needed to be multiplied by 0.472 (i.e., each sung note sped up to be 47.2% as short as the original duration) to make no difference against the spoken description recording, meaning the playback speed of singing should be over 2x faster than the the original recording. Although there are only 5 recording pairs and this measurement does not directly provide the justification for using 0.4 of Cohen's D, we can see how the current SESOI threshold corresponds to the physical attribute of audio by comparing the 4th and 5th columns (106 cents for pitch height and factor of 0.091 for temporal rate in average), which to we authors seems reasonabl borderlines for listeners to notice the change in audio content. The corresponding audio examples are available in our OSF repository (https://osf.io/mzxc8/files/osfstorage/638491c81daa6b1394759086).

Table S1. Overview of our pilot recordings with key features (pitch height [f0] and temporal rate [1/IOI]) manipulated to demonstrate what real examples of song and speech might sound like if they the differences were non-existent ("equivalence") or negligible (as small as our chosen SESOI [Smallest Effect Size Of Interest]).

Vocalizer	Feature	Relative effect (p_{re})	Manipulation to demonstrate SESOI (p_{re} = 0.611)	Manipulation to demonstrate equivalence (p_{re} = 0.5)
D. Sadaphal (Marathi)	f_0	0.992	-730 cents (i.e., pitch is transposed down such that sung pitch is more than half an octave lower than the original)	-860 cents
Nweke (Yoruba)	f_0	0.995	-930 cents	-1030 cents
McBride (English)	f_0	0.931	-650 cents	-770 cents
Hadavi (Farsi)	f_0	0.978	-430 cents	-480 cents
Ozaki (Japanese)	f_0	0.997	-1300 cents	-1430 cents
D. Sadaphal (Marathi)	IOI	0.931	x 0.544 (i.e., playback speed is increased by almost 2x such that the duration of each sung note is only 54.4% as fast as the original)	x 0.472
Nweke (Yoruba)	IOI	0.831	x 0.622	x 0.499
McBride (English)	IOI	0.836	x 0.530	x 0.415

Hadavi (Farsi)	IOI	0.932	x 0.396	x 0.324
Ozaki (Japanese)	IOI	0.939	x 0.393	x 0.320

Appendix 1 Recording protocol

We study how and why song and speech are similar or different throughout the world, and we need your help! We are recruiting collaborators speaking diverse languages who can record themselves singing one short (minimum 30 second) song excerpt, recitation of the same lyrics, spoken description of the song, and an instrumental version of the song's melody. In addition, we ask collaborators to include a transcribed text that segments your words according to the onset of the sound unit (e.g., syllable, note) that you feel reasonable. **The recording/transcription/segmentation process should take less than 2 hours.** (Later we will ask you to check sound recordings that we produce based on your segmented text, which may take up to 2 more hours.)

Collaborators will be **coauthors** on the resulting publication, and will also be **paid a small honorarium** (pending the results of funding applications). In principle, all audio recordings will be published using a CC BY-NC 4.0 non-commercial open access license, but exceptions can be discussed on a case-by-case basis (e.g., if this conflicts with taboos or policies regarding indigenous data sovereignty). We seek collaborators aged **18 and over** who are speakers of diverse 1st/heritage languages.

Once you have finished the recordings and created the segmented text files, please:

- **email us your text files (but NOT your audio recordings) to psavage@sfc.keio.ac.jp and yozaki@sfc.keio.ac.jp.**
- email your **audio recordings to globalsongspeech@gmail.com**, where they will be securely monitored and checked by our RA, Tomoko Tanaka, who is not a coauthor on the manuscript.

This folder shows an example template of one full set of recordings and text files**:**
https://drive.google.com/drive/folders/1qbYpv_gxy-gQTBpATA3WwtPHkj14-lSU?usp=sharing

If you have any questions about the protocol, please email:

- Dr. Patrick Savage (psavage@sfc.keio.ac.jp), Associate Professor, Keio University
- Yuto Ozaki (yozaki@sfc.keio.ac.jp), PhD student, Keio University

---

[Recording content]

- Please choose one traditional song to record. This should be a song you know how to sing that is one of the oldest/ most "traditional" (loosely defined)/ most familiar to your cultural background. This might be a song sung to you as a child by your parents/relatives /teachers, learned from old recordings, etc**.** (we plan to include other genres in future stages). Since there is no universally accepted definition of "song" (which is an issue we hope to address in this study), you are free to interpret "song" however feels appropriate in your language/culture. Please contact us if you would like to discuss any complexities of how to define/choose a "traditional song".

- Please choose a song that you can record yourself singing for a **minimum of 30 seconds**. However, we encourage you to record yourself for as long as makes sense for your song to enable more in-depth future studies without having to go back and re-record yourself (though we request you keep within a maximum of 5 minutes if possible). Note that it is fine if it takes less than 30 seconds to recite the same lyrics when spoken, but please ensure that your free spoken description also lasts a minimum of 30 seconds.

- Please use your **1st/heritage language for every recording** (except for the instrumental track). If you speak multiple languages, please choose one language (and let us know which one ahead of time) and avoid combining multiple languages in singing, recitation and spoken description.

- Please record song, lyric recitation, spoken description and instrumental in the order that you feel natural.

    - **Song:** When you sing, please sing solo without instrumental accompaniment, in a pitch range that is comfortable to you. You do not need to follow the same pitch range sung by others. Feel free to sing while reading lyrics/notation if it is helpful.
    - **Lyric recitation:** When you recite the lyrics, please speak in a way you feel is natural. Feel free to read directly from written lyrics if it is helpful.
    - **Spoken description**: Please describe the song you chose (why you chose it, what you like about it, what the song is about, etc.). However, please avoid quoting the lyrics irn your description. Again, aim for **minimum 30 seconds.**
    - **Instrumental version:** Please also record yourself playing the melody of your chosen song(s). We would be delighted for you to play with a traditional instrument in your culture or country. Continuous-pitch instruments (e.g., violin, trombone, erhu) are especially helpful, but fixed-pitch instruments (e.g., piano, marimba, koto) are fine, too. Please do not use electronic instruments (e.g. electric keyboard). Choose whatever pitch/key is comfortable for you to play (this need not be the same pitch/key as the sung version). Please contact us if you want to discuss any complexities involved in trying to play your song's melody on an instrument.
        - ➢ If you do not play a melodic instrument, it is also acceptable to just record the song's rhythm using tapping sounds or other percussive sounds (e.g., drums). In this case, this "instrumental" recording will only be used to analyze rhythmic features. In this case, you can tap the rhythm while singing in your head, but please do not sing out loud.

[Recording method]

- Please record in a quiet place with minimal background noise.

- Please record each description/recitation/song/instrumental separately as different files. The file name should be "[Given name]_[Surname]_[Language]_Traditional_[Song title]_[YYYYMMDD of the time you record]_[song|recit|desc|inst].[file format]". For example,

    - Yuto_Ozaki_Japanese_Traditional_Sakura_20220207_song.wav
    - Yuto_Ozaki_Japanese_Traditional_Sakura_20220207_recit.wav
    - Yuto_Ozaki_Japanese_Traditional_Sakura_20220207_desc.wav
    - Yuto_Ozaki_Japanese_Traditional_Sakura_20220207_inst.wav

- **Please ensure that your mouth (or instrument) is the same distance from your recording device for each recording, and please make all recordings during one session (to avoid differences in recording environment and/or your vocal condition on that day).**

- Regarding the recording device, a high-quality microphone would be great, but a smartphone or personal computer built-in microphone is also fine. Preferred formats are: .mp4, .MOV, .wav, with sampling rate: 44.1kHz or higher / bit rate: 16bit or higher for .wav and lossless codecs (e.g. Apple Lossless Audio Codec) and 128kbps or higher for .MOV and .mp4 with lossy compression codecs. If you are an iPhone user and considering using the Voice Memos app, please set the "Audio Quality" configuration to "Lossless".

  - Note: although we only require and will only publish audio data for the main study, we have found that default audio quality can be higher when recording video via smartphone than when recording audio. Also, when it comes time to publish the findings with accompanying press releases, we plan to ask for volunteers who want to share videos of their own singing/speaking. So if you want to make your initial recordings using video, it may save time if you decide you want to volunteer video materials later on.

[Segmented texts]

- After the recording of spoken description, lyric recitation or song, please create a Word file or Rich Text Format file per recording that segments your utterance based on the onset of acoustic units (e.g., syllable, note) that you feel natural. It is up to you how you divide song/speech into what kind of sound unit.
  - Technically, we would like you to focus on the perceptual center or "P-center" (Morton, Marcus, & Frankish, 1976), which is "the specific moment at which a sound is perceived to occur" (Danielsen et al., 2019).
  - Segmentation by the acoustic unit of language (e.g. syllable, mora), by the acoustic unit of music (e.g. note, 節 fushi), and by the P-center are not necessarily the same. For example, one syllable may sometimes be sung across multiple notes (and vice versa).
- **Please use a vertical bar (“|”) to segment recordings (see examples below).**
- Please use romanization when writing and also write it based on the phoneme in your native script if it doesn’t use Roman characters. You may use IPA (International Phonetic Alphabet) instead of romanization if you prefer.
- Please start a new line in the segmented text at the position where your utterance has a pause for breathing
- When there are successive sound units that keep the same vowels (e.g. "melisma" in Western music, "kobushi" in Japanese music, etc.) and you feel have separate onsets, then you can segment the text by repeating vowels (e.g. A|men → A|a|a|a|men).
- Please include a written English translation of the text of the spoken description and the sung lyrics.

- Example (Japanese)
  - Singing of Omori Jinku

    (Segmented texts with romanization)
    Ton|Bi|Da|Ko|Na|Ra|Yo|O|O|O
    I|To|Me|Wo|O|Tsu|Ke|E|Te
    Ta|Gu|Ri|Yo|Se|Ma|Su|Yo|O|O
    I|To|Me|Wo|O|Tsu|Ke|E|Te

Hi|Za|Mo|To|Ni|I|Yo|O
Ki|Ta|Ko|Ra|Yoi|Sho|Na

(Original lyrics)
鳶凧ならヨ　糸目をつけて
（コイコイ）
手繰り寄せますヨ　膝元にヨ
（キタコラヨイショナ）

(English translation of the lyrics)
Tie the bridle of a kite kite (Tonbi-dako), pull it in to your knees.
(Kita-ko-ra Yoi-sho-na)

- [Lyrics recitation of Omori Jinku]
  (Segmented texts with romanization)
  Ton|Bi|Da|Ko|Na|Ra|Yo
  I|To|Me|Wo|Tsu|Ke|Te
  Ta|Gu|Ri|Yo|Se|Ma|Su|Yo
  Hi|Za|Mo|To|Ni|I|Yo
  Ki|Ta|Ko|Ra|Yoi|Sho|Na

- Spoken description of Omori Jinku
  (Segmented texts with romanization)
  E-|Wa|Ta|Shi|Ga|E|Ran|Da|No|Ha, |Oo|Mo|Ri|Jin|Ku, |To|Iu, |E-, |Tou|Kyou|No|Min|You|De|Su.
  Oo|Mo|Ri|To|Iu|No|Ha|Tou|Kyou|No|Ti|Mei|De,
  I|Ma|Wa|Son|Na|O|Mo|Ka|Ge|Ha|Na|In|Desu|Ke|Re|Do|Mo
  Ko|No|U|Ta|Ga|U|Ta|Wa|Re|Te|I|Ta|To|Ki|Ha,|Sono,|No|Ri|Ga,|Ni|Hon|De|I|Ti|Ban|To|Re|Ru|Ba |Sho|To|Iu|Ko|To|De,
  Maa|Wa|Ri|To|So|No,|Kai|San|Bu|Tsu|De|Nan|Ka|Yuu|Mei|Na, |Ti|I|Ki|Dat|Ta|Mi|Ta|I|De|Su.
  Kyo|Ku|No|Ka|Shi|Mo,
  E-, |Sou|Des|Ne, |Ho|Shi|Za|Ka|Na, |To|Ka, |Sou|Iu|Ki-|Wa-|Do|Ga|De|Te|Ki|Ma|Su.

  (Original spoken description)
  えー、私が選んだのは、大森甚句、という、えー、東京の民謡です。
  大森というのは東京の地名で、
  今はそんな面影はないんですけれども
  この歌が歌われていたときは、その、海苔が、日本で一番取れる場所ということで、
  まぁ割とその、海産物でなんか有名な、地域だったみたいです。
  曲の歌詞も、
  えー、そうですね、干し魚、とか、そういうキーワードが出てきます。

  (English translation of the spoken description)
  Ah, the song I chose is entitled Omori-Jinku, ah, a Minyo song from Tokyo. Omori is the name of a place in Tokyo, and it has changed a lot these days, but in those days when this song was sung, the place was known for producing the largest amount of nori (seaweed) in Japan, and it also seemed popular due to seafood. Speaking of the lyrics of the song, ah, yeah, like dried fishes, such keywords appear.

- Example (English)

  - Singing of Scarborough Fair
    (Segmented texts with romanization)
    Are |you |go|ing |to |Scar|bo|rough |Fair
    Pars|ley, |sage, |rose|ma|ry |and |thyme
    Re|mem|ber |me |to |one |who |lives |the|ere
    She |once |was |a |true |love |of |mine
    Tell |her |to |make |me |a |cam|b|ric |shirt
    Pars|ley |sage, |rose|ma|ry |and |thyme

With|out |no |seam |or |nee|dle|wo|ork
Then |she’ll |be |a |true |love |of |mine

- Lyrics recitation of Scarborough Fair
  (Segmented texts with romanization)
  Are |you |go|ing |to |Scar|bo|rough |Fair
  Pars|ley, |sage, |rose|ma|ry |and |thyme
  Re|mem|ber |me |to |one |who |lives |there
  She |once |was |a |true |love |of |mine
  Tell |her |to |make |me |a |cam|bric |shirt
  Pars|ley |sage, |rose|ma|ry |and |thyme
  With|out |no |seams |nor |nee|dle|work
  Then |she’ll |be |a |true |love |of |mine

- Spoken description of Scarborough Fair
  (Segmented texts with romanization)
  For |my |tra|di|tio|nal |song |I’m |gon|na |sing |Scar|bo|rough |Fair,|
  um, |be|cause |it |is |one |of |the |ol|dest|
  songs |that |is, |uh, |quite |well |known |be|cause |it |was, |ah, |made |po|pu|lar |by, |ah, |Paul |Si|mon |and |Art |Gar|fun|kle.|
  Um,
  and |it |al|so |has |this |nice |kind |of |haun|ting,|
  beau|ti|ful |me|lo|dy |with |this, |uh, |nice |Do|ri|an |scale |that |gives |it |this |kind |of |old |fa|shioned |feel |that |I |quite |like.|
  And |then |the, |the |mea|ning |is |quite |um, |ah, |In|t’res|ting,|
  has |this |kind |of |strange,|
  um, |im |pos|si|ble |rid|dle |kind |of |theme |where |the,|
  ah, |cha|rach|ter |keeps |as|king |the, |um,|
  o|thers |to |do |these |im|pos|si|ble |things, |so |it’s |kind |of |this|
  cryp|tic, |old|fa|shioned |song |that |I, |ah, |I |quite |like.

- Please save the segmented texts of each description/recitation/song separately as different files. The file name should be "[Given name]_[Surname]_[Language]_Traditional_[Song title]_[YYYYMMDD of the time you record]_[song|recit|desc].[file format]". For example,
  - Yuto_Ozaki_Japanese_Traditional_Sakura_20220207_song.docx
  - Yuto_Ozaki_Japanese_Traditional_Sakura_20220207_recit.docx
  - Yuto_Ozaki_Japanese_Traditional_Sakura_20220207_desc.docx
    - ➢ Therefore, you will upload 7 files in total as your deliverables (i.e. 4 audio files and 3 Word/RTF files) in the end.

Appendix 2 Collaboration agreement form[5]

Collaboration agreement form for "Similarities and differences in a global sample of song and speech recordings"

This project uses an unusual model in which collaborators act as both coauthors and participants. All recorded audio data analyzed will come from coauthors, and conversely all coauthors will provide recorded audio data for analysis. Collaborators will be expected to provide data within 2 months of when these are requested. Please do NOT send data now - we are following a Registered Report model where data must not be collected until the initial research protocol has been peer-reviewed and received In Principle Acceptance. We estimate this will be in early 2023, and ask that you provide your audio recordings and accompanying text within 2 months of In Principle Acceptance. We estimate this recording/annotation will take approximately 1-2 hours to complete. This will be followed by an additional 1-2 hours to check/correct the final files we prepare at a later date.

All collaborators reserve the right to withdraw their coauthorship and data at any time, for any reason, until the manuscript has passed peer review and been accepted for publication. In such cases, their data will be immediately deleted from all computers and servers, public and private (though be aware that if this happens after posting to recognized preprint/data servers such as PsyArXiv or Open Science Framework some data may remain accessible). The corresponding authors (Patrick Savage and Yuto Ozaki) also reserve the right to cancel this collaboration agreement and publish without a given collaborator’s data and coauthorship if necessary (e.g., if data are not provided according to the agreed timeline, or if an insurmountable disagreement about manuscript wording arises). In such a case, any contributions made will be acknowledged in the manuscript.

Collaborators will be coauthors on the resulting publication, and will also be paid a small honorarium (pending the results of funding applications) unless they choose to waive the honorarium. In principle, all audio recordings will be published as supplementary data with this manuscript and permanently archived via recognized preprint/data servers (e.g., PsyArXiv, Open Science Framework, Zenodo) using a CC BY-NC 4.0 non-commercial open access license, but exceptions can be discussed on a case-by-case basis (e.g., if this conflicts with taboos or policies regarding indigenous data sovereignty). We seek collaborators aged 18 and over who speak a diverse range of 1st/heritage languages.

[5] **NB: This agreement had a different timeline from that eventually adopted, because after beginning the process of scheduled review and discussing the issue of confirmation bias with our editor, we concluded that we needed to modify our planned level of bias control from Level 6** ***(“No part of the data that will be used to answer the research question yet exists and no part will be generated until after IPA [In Principle Accepantce] (so-called ‘primary RR’)”)*** **to Level 2** ***(“At least some data/evidence that will be used to answer the research question has been accessed and partially observed by the authors, but the authors certify that they have not yet sufficiently observed the key variables within the data to be able to answer the research question AND they have taken additional steps to maximise bias control and rigour (e.g., conservative statistical threshold, recruitment of a blinded analyst, robustness testing, the use of a broad multiverse/specification analysis, or other approaches for controlling risk of bias)”*****; cf. “Registered Reports with existing data”).**

We thus had to ask collaborators to record themselves several months earlier than they had originally agreed. Most of them managed to do this, but some did not. Because the number of collaborators who could not meet the revised timeline was small enough not to affect our planned power analyses or robustness analyses, we shared the manuscript with all authors and will incorporate those who had not yet made their recordings in the robustness analyses, along with the other authors who made their recordings after knowing the hypotheses.

For analysis, we plan to collect and publish demographic information about each collaborator along with their recordings (language name, city language was learned, biological sex [optional], birth year [optional]). Providing your biological sex or birth year are optional - if you opt not to include these, we will simply exclude your audio data from exploratory analyses that use these variables. (Though please note that biological sex and age may be guessed from your recordings even if you opt not to answer these questions.)

For compliance purposes, CompMusic Lab ("we" or "us") is the data controller of demographic data and audio recordings we hold about you, and you have a right to request information about that data from us (including to access and verify that data). We would like your informed consent to hold and publish demographic data and recordings that you provide to us. All such data will be treated by us under agreed license terms. Please tick the appropriate boxes if you agree and then sign this form:

- □ I agree for my data (audio recordings, written transcriptions, and demographic information [language, city language learned, and biological sex and birth year if provided]) to be used as part of research.
- □ I agree to provide my audio recordings and text annotations within 2 months of the Stage 1 protocol's In Principle Acceptance, and to check/correct the final annotated files within 2 months of their preparation.
- □ I agree to publish my data under a CC BY-NC 4.0 non-commercial open access license.
    a. (If you do not agree to publish your data under CC BY-NC 4.0 [e.g., for reasons relating to Indigenous data sovereignty]) please state your conditions for sharing your audio recording data.:_______________
- □ I agree to be a coauthor of the manuscript.
- □ I agree for a preprint of the manuscript and accompanying data to be posted to recognized preprint/data servers (e.g., PsyArXiv, Open Science Framework, Zenodo).

If you would like to waive the honorarium, you can also tick this box. If you do not waive the honorarium, we will contact you separately to provide bank account details for the wire transfer after you have provided all data.

- □ I choose to waive the honorarium

Name: ____
Affiliation (e.g., Department, University, Country): __________________________________
1st/heritage language(s) spoken: ____
Primary city/town/village(s) where language(s) were learned: ___________________________
[Optional] Biological sex (e.g., male, female, non-binary, etc.):___________________________
[Optional] Birth year: ____

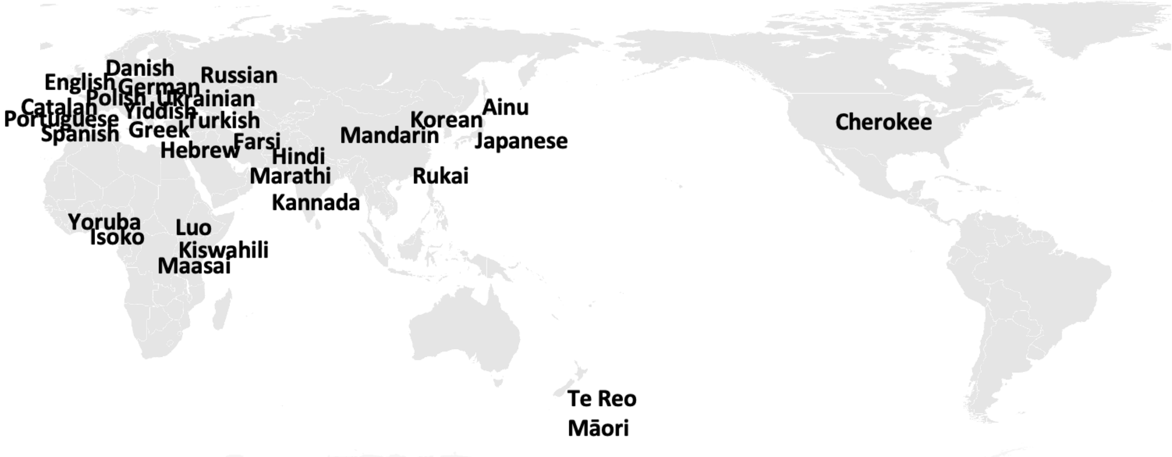
Appendix 3: Open call for collaboration to the International Council for Traditional Music (ICTM) email list. Adapted versions of this email were also used later in tandem with in-person recruitment at the conferences described in the main text). Note that in later meetings we decided to relax the restriction of one collaborator per language, in part due to difficulties of defining the boundaries separating languages and the desire to maximize inclusion.

From: Patrick Savage <psavage@sfc.keio.ac.jp>
Subject: Call for collaboration on global speech-song comparison
Date: July 15, 2022 9:49:57 JST
To: "ictm-l@ictmusic.org" <ictm-l@ictmusic.org>

Dear ICTM-L members,

I am emailing to inquire if any of you are interested in collaborating on a project comparing speech and song in diverse languages around the world to determine what, if any, cross-culturally consistent relationships exist.

I mentioned this project briefly back in January in response to the discussion about Don Niles' post to this list entitled "What is song?". Since then, we have recruited several dozen collaborators speaking diverse languages (see attached rough map), but would like to open up the call to recruit more. As you can see from the map, our current recruitment is quite unbalanced, particularly lacking speakers of indigenous languages of the Americas, Oceania, and Southeast Asia. We hope you can help us correct that!



Collaborators will be expected to make short (~30 second) audio recordings of themselves in four ways:
1) singing a traditional song in their native language
2) reciting the lyrics of this song in spoken form
3) describing the meaning of the song in their native language
4) performing an instrumental version of the song's melody on an instrument of their choice (negotiable)
They will also provide written transcriptions of these recordings, segmented into acoustic units (e.g., syllables, notes) and English translations. Later, they will check/correct versions of these recordings created by others with click sounds added to the start of each acoustic unit. Finally, they will help us interpret the results of acoustic comparisons of these recordings/annotations. Our pilot studies suggest that this should all take 2-4 hours for one set of 4 recordings.

Collaborators will be coauthors on the resulting publication, and will also be paid a small honorarium (pending the results of funding applications). In principle, all audio recordings will be published using a CC BY-NC non-commercial open access license, but exceptions can be discussed on a case-by-case basis (e.g., if this conflicts with taboos or policies regarding indigenous data sovereignty).

We seek collaborators aged 18 and over who are native speakers of diverse languages, but we are open to collaborators who are non-native speakers in cases of endangered/threatened languages where there are few native speaker researchers available. During this first stage, we only plan to recruit one collaborator per language, on a first-come first-served basis in principle (in future stages we will recruit multiple speakers per language).

More details and caveats (e.g., how to interpret "traditional" or "song") can be found in a draft protocol here:

https://docs.google.com/document/d/1qICFXwew7OEj06dkSoR59TIF7HCmVGcudkenMwHRemM/edit

We actually are not quite ready to begin the formal recording/analysis process yet as we are still working out some methodological and conceptual issues (for which we would also welcome your contributions). The reason I am putting out this call now is that I will be presenting at ICTM in Lisbon next week and I know many of you will also be there, so I wanted to use this chance to reach out in case any of you want to meet and discuss in person in Lisbon.

I'll be mentioning more details about this project briefly during a joint ICTM presentation on "Building Sustainable Global Collaborative Networks" at 9am on July 26th (Session VIA01), and would be delighted to meet anyone interested in collaboration following this session or at any other time during the week of the conference.

Please email me (mentioning your native language[s]) if you're interested in collaborating or in meeting in Lisbon to discuss possibilities!

Cheers,

Pat

Dr. Patrick Savage (he/him)
Associate Professor
Faculty of Environment and Information Studies
Keio University SFC (Shonan Fujisawa Campus)
http://compmusic.info

B. Stage 2 Supplementary Materials of Chapter 3

S8. Break annotation

Break is defined as the end of a continuous sequence of sounds before relatively long pauses. Breaks are used to avoid creating inter-onset intervals that do not include sounds. For vocal recordings, that would typically constitute when the participant would inhale. In the case of instrumental recordings, how to determine break points between instrumental phrases is up to the person who made the recording, but it is expected to indicate pauses during sound production.

S9. Exploratory Analysis

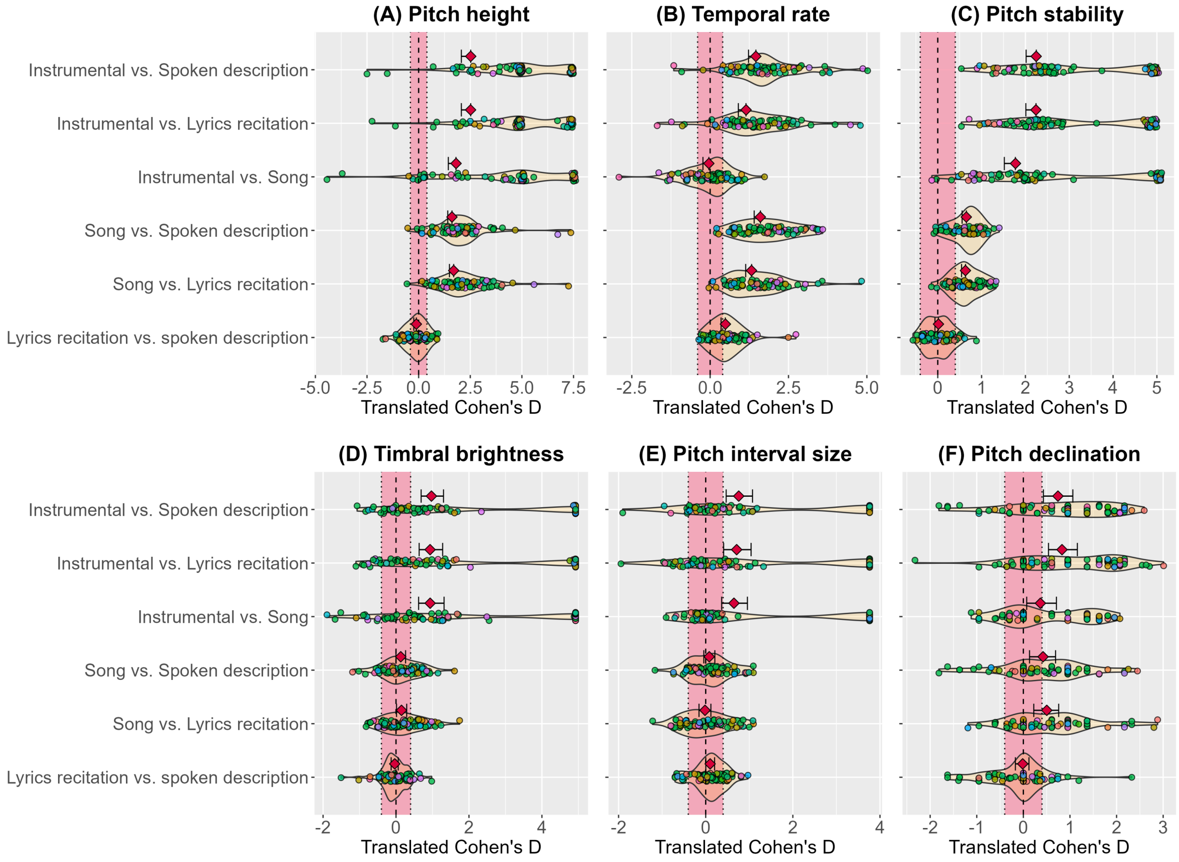


Figure S13. Effect sizes of each feature using the same data as in Figure 3.5 but with exploratory comparisons with recitation and instrumental recording types.

Table S2. Nonparametric trend test (Jonckheere-Terpstra test) for the shift of mean values of features across different acoustic forms. The category is ordered as 1 = instrumental, 2 = song, 3 = lyrics recitation, and 4 = spoken description. Note that the Jonckheere-Terpstra test assumes observations in each category to be independent of the other categories (e.g., between-subjects design), but our data are collected in a within-subjects design. Therefore, the p-values can be somewhat inaccurate in testing the null hypothesis (i.e., H_0: $\theta_1 = \theta_2 = \theta_3 = \theta_4$) if there is a strong correlation within subjects. The p-values were calculated by a Monte Carlo permutation procedure.

Feature	JT statistics	P-value
Pitch height	6752	1.2×10^{-4}
Temporal rate	27672	1.2×10^{-4}
Pitch stability	3569	1.2×10^{-4}
Timbral brightness	16864	1.2×10^{-4}
Pitch interval size	13340	0.30
Pitch declination	10288	1.2×10^{-4}
Phrase length	10876	1.2×10^{-4}
Intensity	13787	3.7×10^{-4}
TImbral noisiness	22998	1.2×10^{-4}
Rhythmic regularity	23484	1.2×10^{-4}
Pitch interval regularity	20329	1.2×10^{-4}
Pulse clarity	9911	1.2×10^{-4}
Pitch range	13114.5	0.20

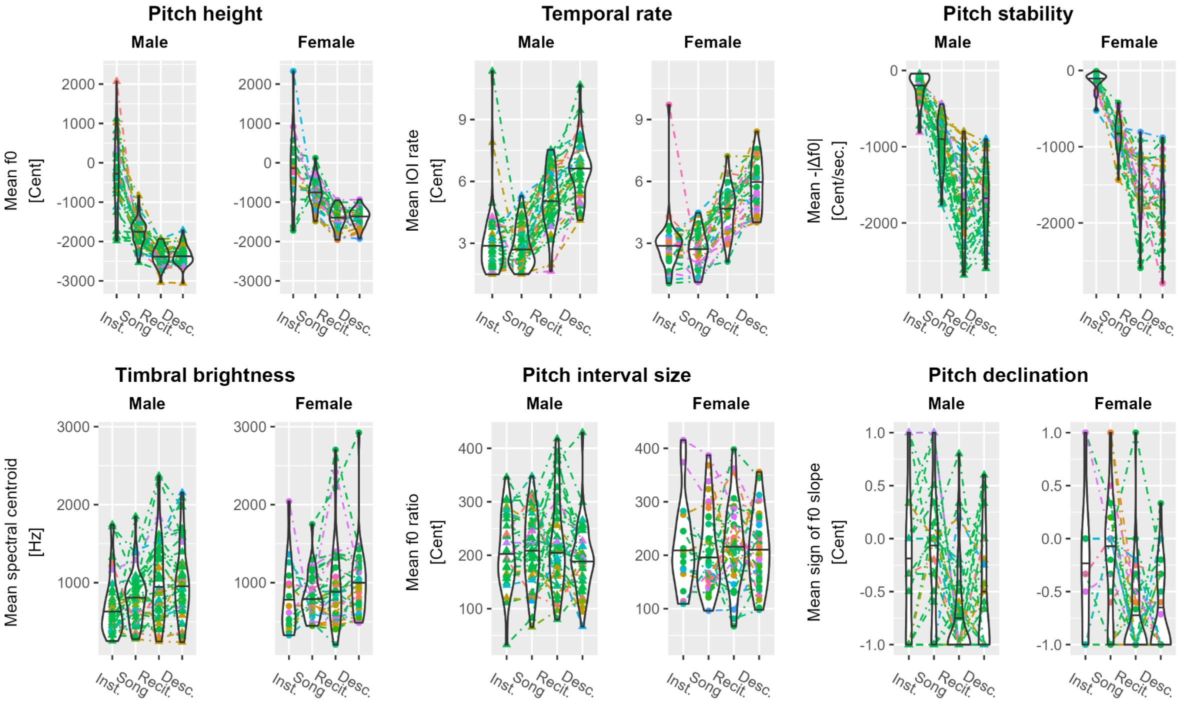


Figure S14. Alternative visualization of Figure 3.9 showing mean values of each feature by biological sex and focusing on the features subject to the main confirmatory analysis. Note that the colors of data points indicate language families, which are coded the same as in Figure 3.3.

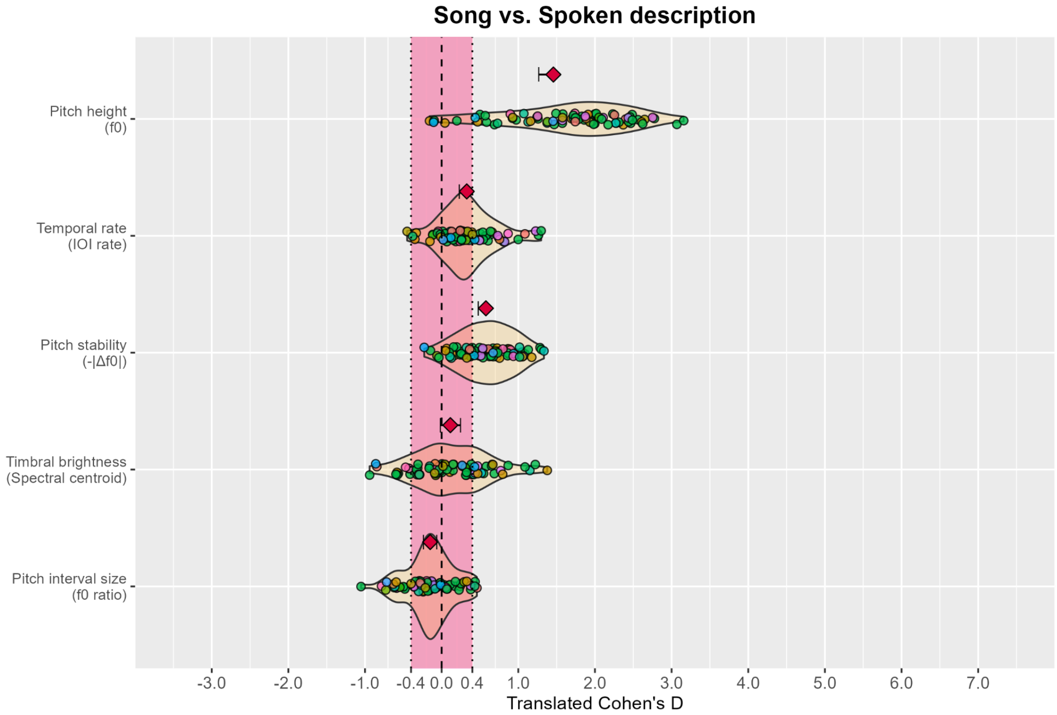


Figure S15. Re-running of the analysis on our full data with automated feature extraction. pYIN (Mauch & Dixon, 2014) was used for f0 extraction and de Jong & Wemp's (2009) Praat script was used for onset timing extraction. Break annotation was not automated so pitch declination was not measured.

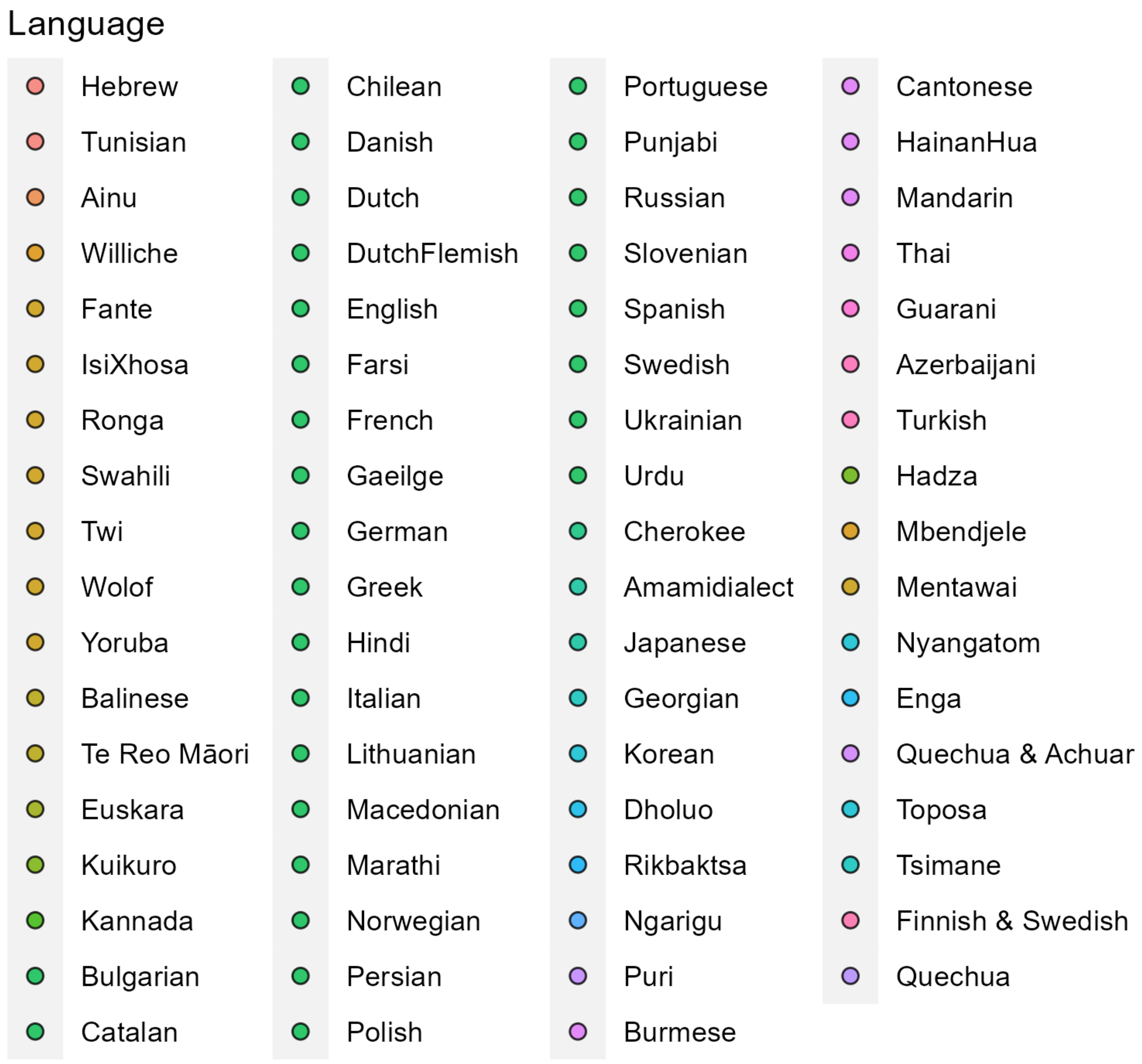


Figure S16. Color mapping of Figure 3.12.

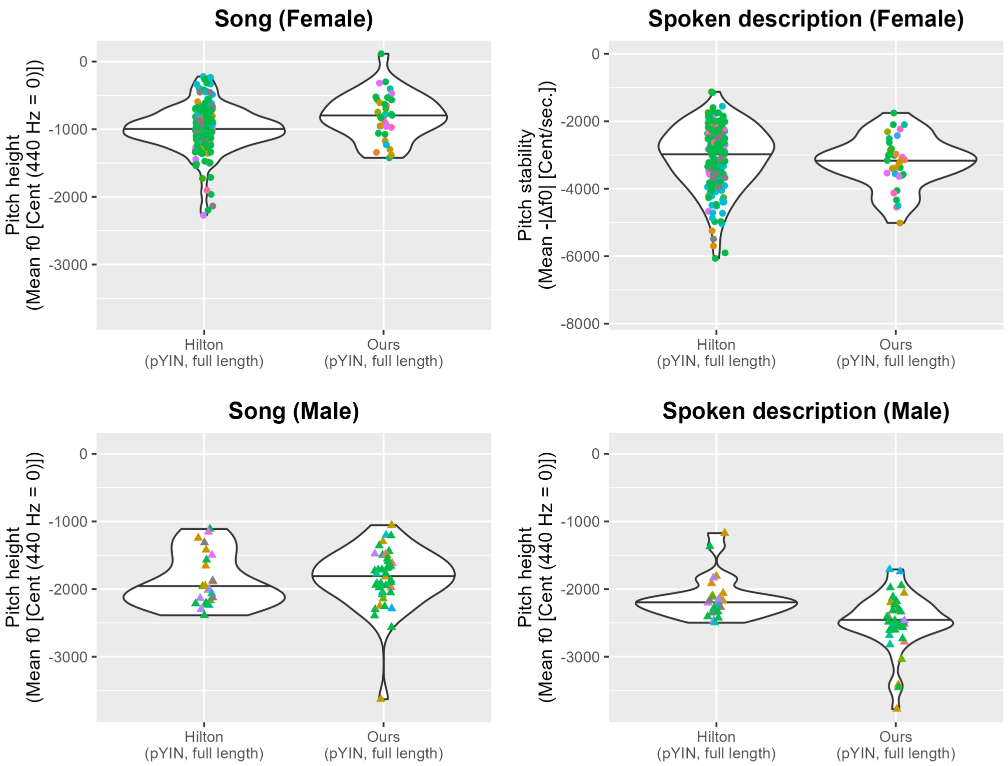


Figure S17. Supplementary information for Fig. 3.10. Mean values of pitch height of each recording are displayed. f_0s were extracted by pYIN (Mauch & Dixon, 2014). The horizontal lines in the violin plots are median.

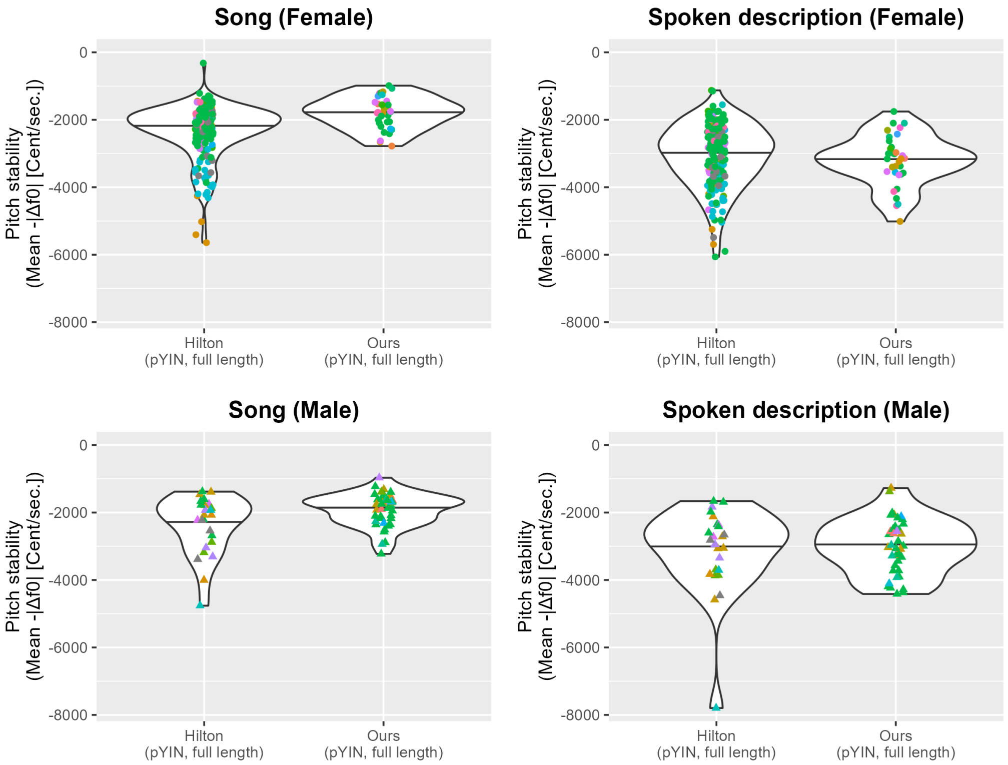


Figure S18. Supplementary information for Fig. 3.10. Mean values of pitch stability of each recording are displayed. f_0s were extracted by pYIN (Mauch & Dixon, 2014). The horizontal lines in the violin plots are median.

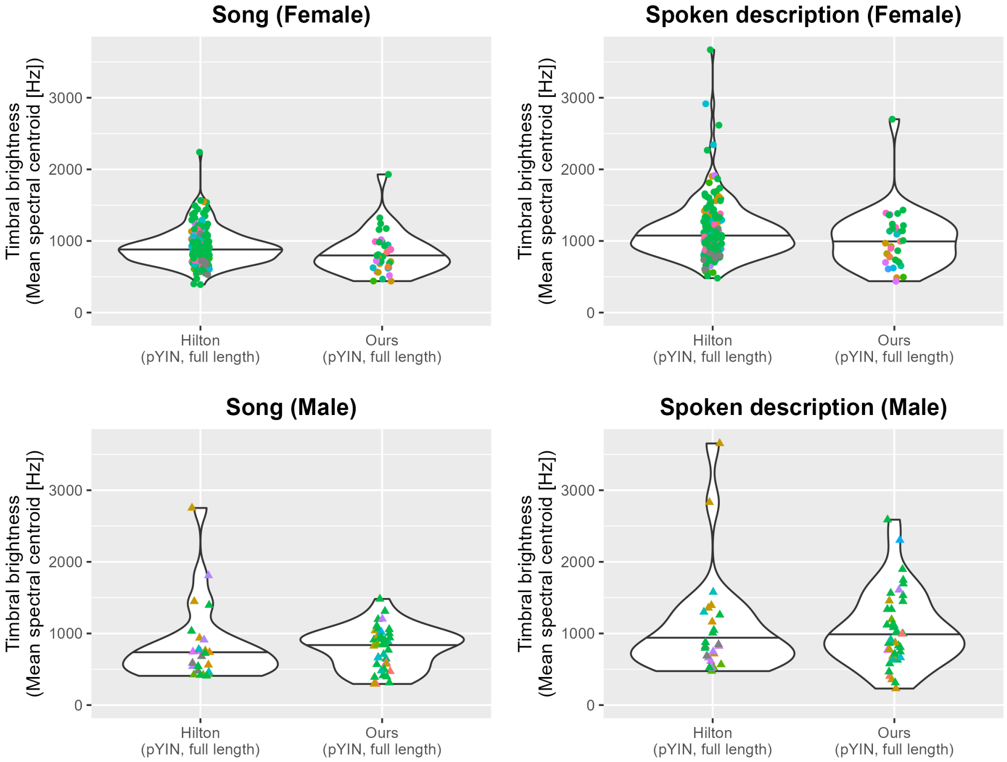


Figure S19. Supplementary information for Fig. 3.10. Mean values of timbral brightness of each recording are displayed. f_0s were extracted by pYIN (Mauch & Dixon, 2014). The horizontal lines in the violin plots are median.

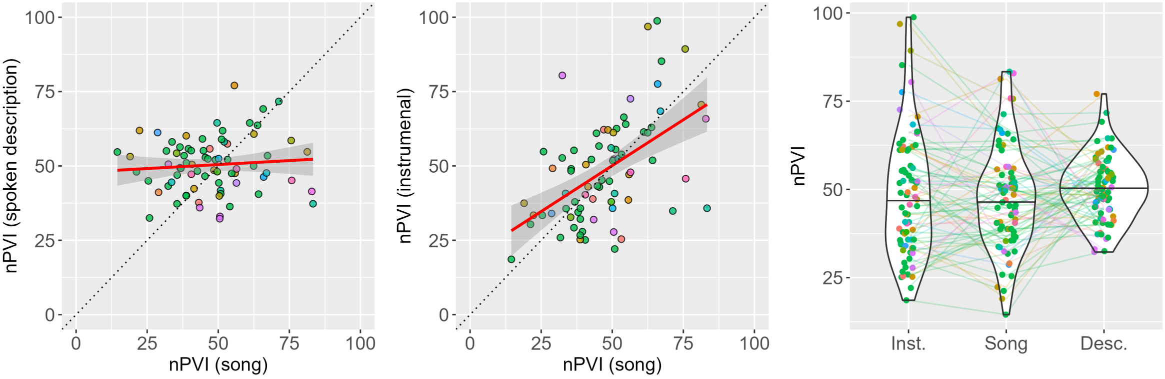


Figure S20. Mapping data by nPVIs of song and spoken description by each collaborator and its song-instrumental version, and the density plot of nPVIs of each . The red lines are linear fitting of nPVIs of spoken description and nPVIs of song, and the dotted line is y = x which can be used to grasp if nPVIs of spoken description is larger than that of song and vice versa.

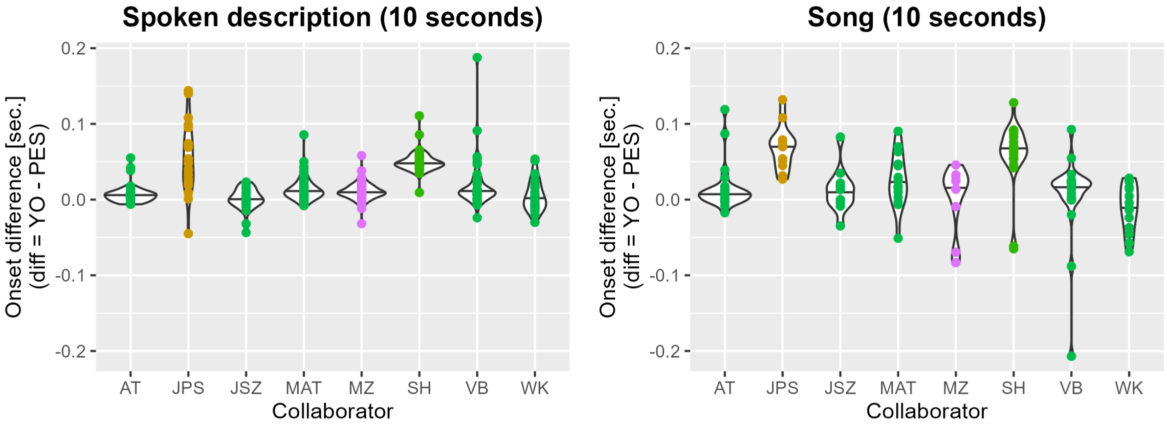


Figure S21. Difference between onset times annotated by YO and onset times annotated by PES per recording. The horizontal lines in the violin plots indicate the median. Color is coded as the same in Fig. 3.3.

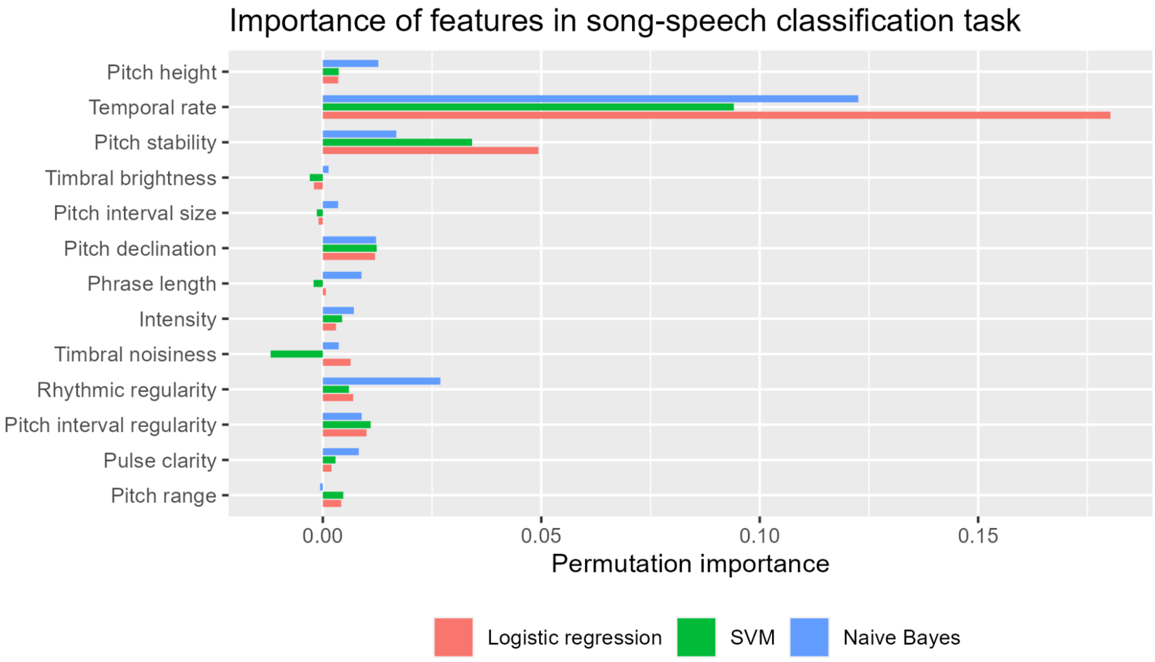
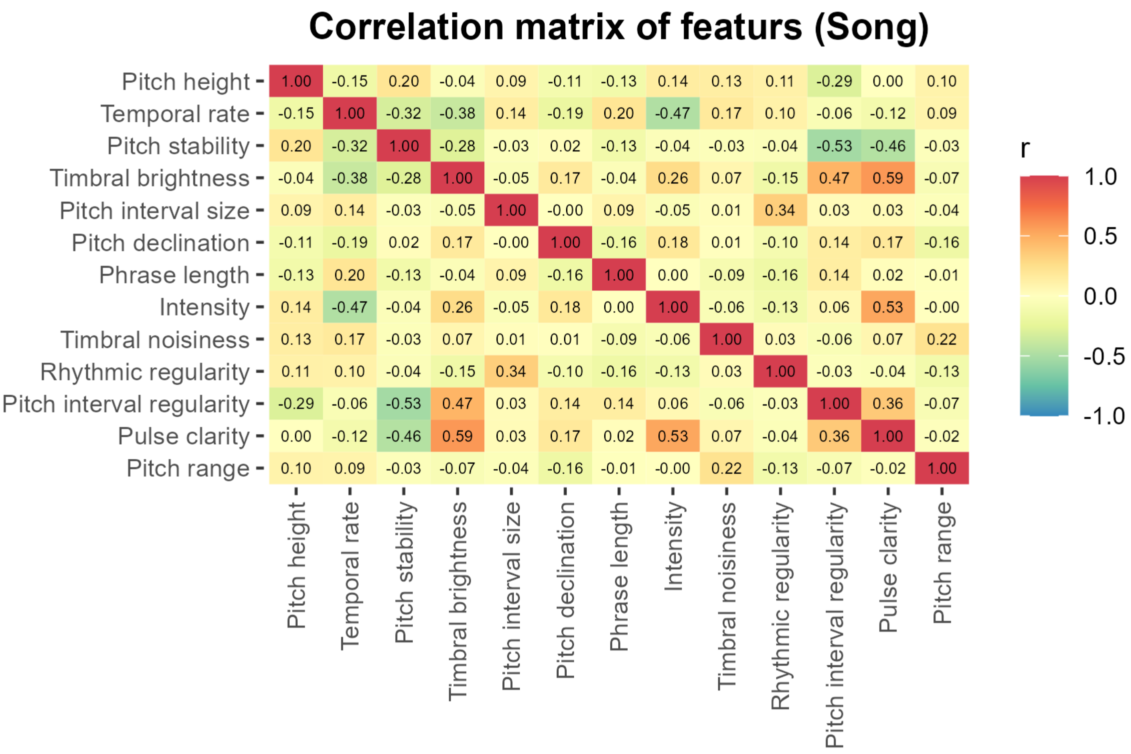


Figure S22. Permutation importance of the features in three binary classifiers.

Table S3. Average over performance metrics measured by randomly splitting recording sets into training and test sets 1024 times.

		Logistic regression	SVM	Naive Bayes
Accuracy		95.78%	93.75%	92.94%
Song	Precision	96.66	92.68	92.81
	Recall	95.25	95.70	93.98
	F1 score	95.72	93.92	93.03
Spoken description	Precision	95.74	95.89	94.45
	Recall	96.31	91.80	91.91
	F1 score	95.80	93.50	92.76



Correlation matrix of featurs (Song)

	Pitch height	Temporal rate	Pitch stability	Timbral brightness	Pitch interval size	Pitch declination	Phrase length	Intensity	Timbral noisiness	Rhythmic regularity	Pitch interval regularity	Pulse clarity	Pitch range
Pitch height	1.00	-0.15	0.20	-0.04	0.09	-0.11	-0.13	0.14	0.13	0.11	-0.29	0.00	0.10
Temporal rate	-0.15	1.00	-0.32	-0.38	0.14	-0.19	0.20	-0.47	0.17	0.10	-0.06	-0.12	0.09
Pitch stability	0.20	-0.32	1.00	-0.28	-0.03	0.02	-0.13	-0.04	-0.03	-0.04	-0.53	-0.46	-0.03
Timbral brightness	-0.04	-0.38	-0.28	1.00	-0.05	0.17	-0.04	0.26	0.07	-0.15	0.47	0.59	-0.07
Pitch interval size	0.09	0.14	-0.03	-0.05	1.00	-0.00	0.09	-0.05	0.01	0.34	0.03	0.03	-0.04
Pitch declination	-0.11	-0.19	0.02	0.17	-0.00	1.00	-0.16	0.18	0.01	-0.10	0.14	0.17	-0.16
Phrase length	-0.13	0.20	-0.13	-0.04	0.09	-0.16	1.00	0.00	-0.09	-0.16	0.14	0.02	-0.01
Intensity	0.14	-0.47	-0.04	0.26	-0.05	0.18	0.00	1.00	-0.06	-0.13	0.06	0.53	-0.00
Timbral noisiness	0.13	0.17	-0.03	0.07	0.01	0.01	-0.09	-0.06	1.00	0.03	-0.06	0.07	0.22
Rhythmic regularity	0.11	0.10	-0.04	-0.15	0.34	-0.10	-0.16	-0.13	0.03	1.00	-0.03	-0.04	-0.13
Pitch interval regularity	-0.29	-0.06	-0.53	0.47	0.03	0.14	0.14	0.06	-0.06	-0.03	1.00	0.36	-0.07
Pulse clarity	0.00	-0.12	-0.46	0.59	0.03	0.17	0.02	0.53	0.07	-0.04	0.36	1.00	-0.02
Pitch range	0.10	0.09	-0.03	-0.07	-0.04	-0.16	-0.01	-0.00	0.22	-0.13	-0.07	-0.02	1.00

Figure S23. Correlation matrix of the features within song recordings. The data are the mean values of the features, which are plotted in Figure 3.6.

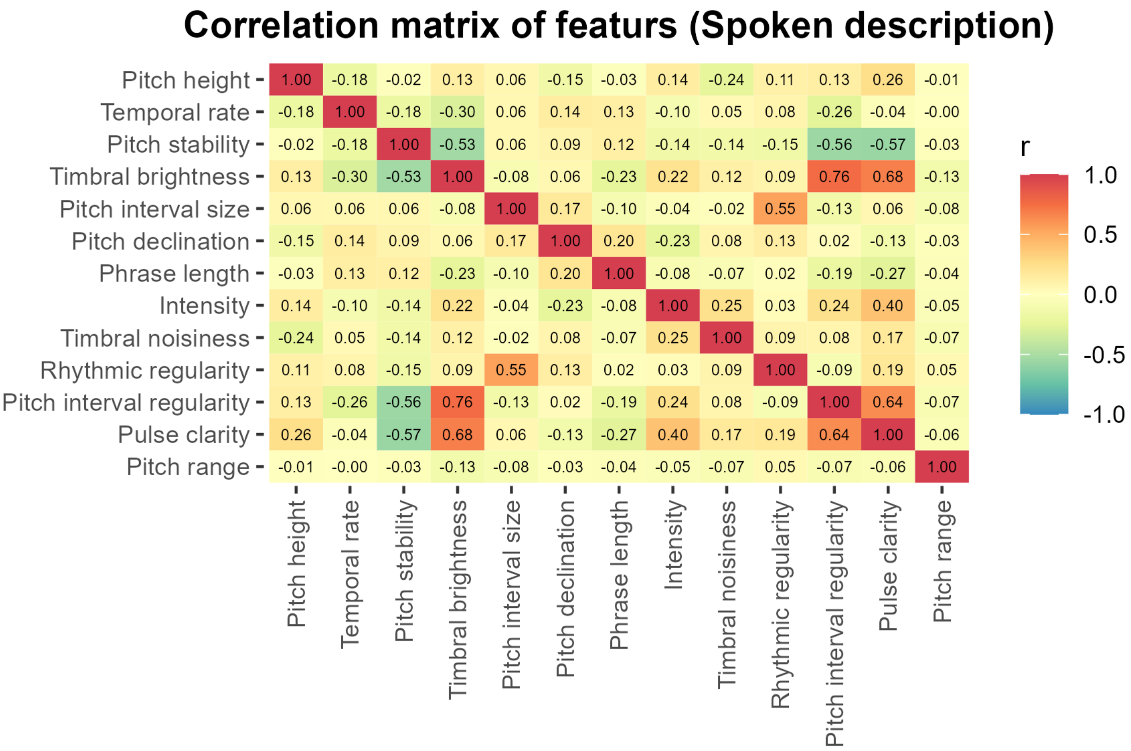


Figure S24. Correlation matrix of the features within spoken description recordings. The data are the mean values of the features, which are plotted in Figure 3.6.

Appendix 3 List of songs

#	Name	Song title (Romanization)	Language	Instrument
1	Nori Jacoby	Laila Laila	Modern Hebrew [Jerusalem]	Whistle
2	Limor Raviv	ירושלים של זהב (Yerushalayim ShelZahav)	Modern Hebrew [Tel Aviv]	Tapping
3	Iyadh El Kahla	لاموني اللي غاروا مني	Tunisian Arabic	Aerophone
4	Utae Ehara	イタサン (Itasan)	Aynu (Hokkaido Ainu)	Tapping
5	Neddiel Elcie Muñoz Millalonco	Ñaumen pu llauken	Tsesungún (Huilliche)	Clapping
6	Nozuko Nguqu	Ulele	IsiXhosa (Xhosa)	Piano
7	Mark Lenini Parselelo	Lala Mtoto Lala	Kiswahili (Swahili)	Tapping
8	Cristiano Tsope	Hiya Tlanguela xinwanana xinga pswaliwa namuntla	Ronga	Clapping
9	Florence Nweke	Pat omo o	Yoruba	Piano
10	Adwoa Arhine	Yɛyɛ Eguafo	Fante (Akan)	Clapping
11	Jehoshaphat Philip Sarbah	Daa na se	Twi (Akan)	Piano
12	Latyr Sy	Mbeuguel	Wolof	Clapping
13	I Putu Gede Setiawan	Putriceningayu	Balinese	Suling
14	Suzanne Purdy	Pōkarekare Ana	Te Reo Māori (Māori) [Auckland]	Tapping
15	Rob Thorne	Ko Te Pū	Te Reo Māori (Māori) [Wellington]	Kōauau rākau
16	Nerea Bello Sagarzazu	Xoxo Beltza	Euskara (Basque) [Hondarribia]	Aerophone
17	Urise Kuikuro	Toló	Língua Kuikuro (Kuikúro-Kalapálo)	Clapping
18	Shantala Hegde	Moodala Maneya	Kannada	Clapping
19	Rytis Ambrazevičius	Sėjau rugelius	Lithuanian	Idiophone
20	Tadhg Ó Meachair	Éiníní	Gaeilge (Irish)	Piano Accordion
21	Niels Chr. Hansen	I Skovens Dybe Stille Ro	Danish	Piano
22	Mark van Tongeren	Hoor De Wind waait	Dutch [Heemstede]	Piano
23	Kayla Kolff	Dikkertje Dap	Dutch [Nairobi]	Membranophone
24	Adam Tierney	Simple Gifts	English [Indiana]	Electric Piano
25	Christina Vanden	Sleep Now Rest Now	English [Michigan]	Cello

	Bosch der Nederlanden			
26	Patrick Savage	Scarborough Fair	English [Nevada]	Piano
27	John McBride	Arthur McBride	English [Newry]	Flute
28	William Tecumseh Fitch	Rovin’ Gambler	English [Pennsylvania]	Guitar
29	Peter Pfordresher	America the Beautiful	English [Washington D.C.]	Piano
30	Yannick Jadoul	VandaagIs't Sinte Maarten	Flemish (Dutch)	Piano
31	Felix Haiduk	Die Gedanken Sind Frei	German	Melodica
32	Ulvhild Færøvik	Nordmannen	Norwegian	Clapping
33	Daniel Fredriksson	Ho Maja	Svenska (Swedish)	Offerdalspipa
34	Emmanouil Benetos	Saranta Palikaria	Greek	Clapping
35	Dhwani P. Sadaphal	Saraswatee maateshwaree	Hindi	Harmonium
36	Parimal M. Sadaphal	Sukhakartaa	Marathi	Sitar
37	Meyha Chhatwal	ਬਾਜਰੇ ਦਾ ਸਿੱਟਾ (Bajre Da Sitta)	Punjabi (Eastern Panjabi)	Harmonium
38	Ryan Mark David	Dil Dil Pakistan	Urdu	Acoustic guitar
39	Shahaboddin Dabaghi Varnosfaderani	Morgh e Sahar	Western Farsi [Isfahan]	Clapping
40	Shafagh Hadavi	Mah Pishanoo	Western Farsi [Tehran]	Piano
41	Manuel Anglada-Tort	La Presó de Lleida	Catalan	Piano
42	Pauline Larrouy-Maestri	À la claire fontaine	French	Piano
43	Andrea Ravignani	Bella Ciao	Italian	Saxophone
44	Violeta Magalhães	O milho da nossa terra	Portuguese [Porto]	Tapping
45	Camila Bruder	A Canoa Virou	Portuguese [São Paulo]	Tambourine
46	Marco Antonio Correa Varella	Suite do Pescador	Portuguese [São Paulo]	Nose flute
47	Juan Sebastián Gómez-Cañón	El pescador	Spanish [Bogotá]	Guitar
48	Martín Rocamora	Aquello	Spanish [Montevideo]	Guitar
49	Javier Silva-Zurita	Un gorro de lana	Spanish [Santiago]	Guitar
50	Ignacio Soto-Silva	El Lobo Chilote	Spanish [Osorno]	Clapping
51	Dilyana Kurdova	Zarad tebe, mome, mori	Bulgarian	Clapping
52	Aleksandar Arabadjiev	Jovano	Macedonian	Kaval

53	Wojciech Krzyżanowski	Wlazł Kotek Na Płotek	Polish	Guitar
54	Polina Proutskova	Dusha moia pregreshnaia	Russian	Violin
55	Vanessa Nina Borsan	En Hribček Bom Kupil	Slovenian	Tapping
56	Olena Shcherbakova	Podolyanochka	Ukrainian	Piano
57	Diana Hereld	ᎤᏁᎳᏅᎯ ᎤᏪᏥ (unelanvhi uwetsi)	Cherokee	Tapping
58	Gakuto Chiba	津軽よされ節 (Tsugaru-yosarebushi)	Japanese [Hokkaido]	Tsugaru-shamisen (津軽三味線)
59	Shinya Fujii	デカンショ節 (Dekansho-bushi)	Japanese [Hyogo]	Clapping
60	Yuto Ozaki	大森甚句 (Omori-Jinku)	Japanese [Tokyo]	Guitar
61	Naruse Marin	朝花節 (Asabana-bushi)	Northern Amami-Oshima	Sanshin (三線)
62	Teona Lomsadze	Nana (Lullaby)	Georgian	Chonguri
63	Sangbuem Choo	아리랑 (Arirang)	Korean	Guitar
64	Patricia Opondo	Ero Okech Nyawana	Luo (dholuo) (Luo (Kenya and Tanzania))	Whistle
65	Rogerdison Natsitsabui	Jakara Wata	Rikbaktsa	Clapping
66	Jakelin Troy	Gundji gawalgu yuri	Ngarigu	Percussion
67	Tutushamum Puri Righi	Petara	Puri Kwaytikindo (Puri)	Terara (bamboo flute)
68	Su Zar Zar	Mya Man Giri	Myanmar (Burmese)	Saung-gauk
69	Psyche Loui	梁祝 (Butterfly Lovers)	Cantonese (Yue Chinese)	Violin
70	Minyu Zeng	五指山歌 (The Song of the Five-Fingers Mountain)	HainanHua (Min Nan Chinese)	Idiophone
71	Fang Liu	送别 (Farewell)	Mandarin Chinese	Clapping
72	Great Lekakul	ลาวดวงเดือน (Lao Doung Duan)	Thai	"Klui"(ขลุ่ย) (a Thai flute)
73	Brenda Suyanne Barbosa	Apykaxu	Mbyá-Guaraní	Clapping
74	Polina Dessiatnitchenko	Ay Lachin	North Azerbaijani	Tar
75	Olcay Muslu	Uzun Ince Bir Yoldayim	Turkish	Tapping