

# Re(de)fining Sonification: Project Classification Strategies in the Data Sonification Archive

PERMAGNUS LINDBORG,<sup>1,\*</sup> VALENTINA CAIOLA,<sup>1</sup> PAOLO CIUCCARELLI,<sup>2,3</sup>  
 (pm.lindborg@cityu.edu.hk) (vcaiola2-c@my.cityu.edu.hk) (p.ciuccarelli@northeastern.edu)

MANNI CHEN,<sup>1</sup> AND SARA LENZI<sup>4,5</sup>  
 (mannichen2-c@my.cityu.edu.hk) (sara.lenzi@deusto.es)

<sup>1</sup>*SoundLab, School of Creative Media, City University of Hong Kong, Hong Kong SAR, China.*

<sup>2</sup>*Center for Design, Northeastern University, Boston, MA.*

<sup>3</sup>*Design Department, Politecnico di Milano, Milano, Italy.*

<sup>4</sup>*Ikerbasque, Basque Foundation for Science, Bilbao, Spain.*

<sup>5</sup>*Faculty of Engineering, Universidad de Deusto, Bilbao, Spain.*

This study focuses on a corpus of 445 sonification projects currently available in the Data Sonification Archive (DSA). The DSA develops in a collaborative process that involves researchers and creative communities and has been online since early 2021. Projects are heuristically classified according to several aspects, in particular their intended purpose, targeted users, subject matter, sonification method, and combination of media. In the present study, the authors analyze six curatorial classification strategies, labelled *Goal*, *Method*, *User*, *Macro Topic*, *Micro Topic*, and *MediaMix*, and discuss their definitions and usefulness for the archive. They then introduce two computational classification strategies, respectively based on clustering of music information retrieval of sonification audio and topic modeling of the descriptive texts that accompany DSA projects. Correlation analysis between curatorial and computational classifications, correspondingly sized, showed that the text-based method was more powerful than the audio-based methods. The authors then explored predictive modeling, tentatively achieving results for *Goal*, *Method*, and *Macro Topic*. This points toward the potential for automatic classification to assist in the curatorial management of the archive, as well as for similar repositories. The discussion focuses on how analysis of classification strategies supports a broadening of the definition of sonification, both as theoretical construct and as practice, where the communicative intention of the author, the aesthetic quality of the listening experience, a more explicit focus on narrative patterns, and other emerging aspects within sonification design, are all contributing factors to transitioning the field toward a mass medium for data representation, communication, and meaning-making.

## 0 INTRODUCTION

In her entertaining and compelling work *Lobbying for the Ear*, Supper dedicates a full chapter [1] to a historical review and exploration of the various successive definitions of data sonification since the foundation of the International Community on Auditory Display (ICAD) in 1992. In the first ICAD Proceedings (1994), Scaletti attempted to define and delimit the boundaries of the new discipline [2]. She defined data sonification as “A mapping of numerically represented relations in some domain under study to relations in an acoustic domain for the purposes of interpreting,

understanding, or communicating relations in the domain under study.” Already in 1991, she had provided a working definition describing sonification as a way to address the “general problem of how sound can be used to assist the human analyst in the interpretation of a wide variety of data” [3]. In a more recent contribution [4], she defined sonification as “a mapping from data generated by a model, captured in an experiment, or otherwise gathered through observation, to one or more parameters of an audio signal or sound synthesis model, for the purpose of better understanding, communicating or reasoning about the original model, experiment or system.” These definitions focus, on the one hand, on the physical nature of sound (i.e., “acoustic relations” and “audio signal”), and, on the other hand, the purpose of sonification, which (since the 1994 definition)

\*To whom correspondence should be addressed, email: pm.lindborg@cityu.edu.hk. Last updated: July 22, 2024.

highlights the interpretation of data, understanding of a phenomenon, and/or communication with an audience. A third element, which, however, tends to disappear in later definitions, seems to limit the field to data that can be represented numerically, thus excluding qualitative data or data that are represented semantically (such as data retrieved from the web, which is currently a large area of investigation in the representation of data).

The two concepts of *materiality*, “sound as a parameterizable acoustic phenomenon,” and *intent*, “purposes of interpretation, understanding and communication,” are also at the core of the definition by Kramer and collaborators in the seminal “Sonification Report” [5], a collaborative effort redacted for the U.S. National Research Council by the members of the then recently founded ICAD. Here, sonification is “the use of non-speech audio to convey information. More specifically, sonification is the transformation of data relations into perceived relations in an acoustic signal for the purposes of facilitating communication or interpretation.” In this definition, human perception emerges as the mediator between perceived relationships in the data and designed relationships in the acoustic phenomenon, thus opening the door to psychoacoustics in the design of sonification. A certain ambiguity between acoustics and psychoacoustics descriptors in the definitions of sonification has characterized the field since its inception; this was discussed and addressed in a recent contribution [6]. At the same time, the authors of the “Sonification Report” limited the scope of allowable raw materials for the sonification designer by explicitly excluding speech. This decision has, in practice, influenced the field to focus more on *materiality* than *intent*.

Kramer’s definition was not exempt from criticism. Hermann highlighted the contribution of speech, in particular the prosodic attributes of speech, as a “valuable element in auditory display” [7]. Additionally, he proposed the introduction of several criteria to assess what can be rightly called a sonification [8], further delimiting the field of application to acoustic representations that reflect objective properties of data, in which the transformation from data to sound is *systematic*, results are *reproducible*, and a same sonification system can be used with different datasets (i.e., it is *generalisable*). Meanwhile, Barrass defines sonification as “the design of sounds to support an information processing activity” [9], for which attention to the aesthetic quality of the auditory experience of the listener is critical [10]. These somewhat contradictory characterizations of sonification and what it can achieve evidence two complimentary approaches, that the authors label as *utilitarian* (i.e., discovery-oriented, engineering-directed, *ars informatica*) and *hedonistic* (i.e., experience-oriented, artist-directed, *ars musica*).

While introducing the importance of design methods and aesthetic quality in the sonification process, these concepts also act to broaden its boundaries to embrace activities that involve the production of information: The goal of sonification is to process and transform data into information to ultimately create knowledge [11]. Worrall again places the accent on knowledge: “Sonification is the acoustic repre-

sentation of data for relational interpretation by listeners, for the purpose of increasing their knowledge of the source from which the data was acquired” [12]. His definition highlights the difference between the dataset and the phenomenon behind the data and situates the listener at the core of the meaning-making process that sonification facilitates. In 2015, Roddy defined sonification from an embodied knowledge perspective as “the systematic data-driven generation of non-speech sound to communicate information about a data source to an embodied listener, who is tasked with perceiving the appropriate meaning(s) within, and/or assigning the appropriate meaning(s) to, that sound” [13]. Again, an aesthetic approach to the listening experience is critical to support the listener’s meaning-making process [14].

Attention to crossmodal association mechanisms in the design of appropriate embodied metaphors, relating data properties to sonic properties, was discussed in [15]. This attempt at defining “ground rules” for successful sonification was probed further in a recent study by Groß-Vogt and collaborators [16]. While they focused on scientific publications in order “to study a more complete and less human-biased data-set,” the present authors believe it is essential for sonification, as a broad and inclusive field of activity, to embrace knowledge from electroacoustic music composition [17, 18] and aesthetics [19] as central to the meaning-making process. Followingly, Liew and Lindborg [20] put forth an inclusive definition of sonification as “any technique that translates data into non-speech sound, with a systematic, describable, and reproducible method, to reveal or facilitate communication, interpretation, or discovery of meaning that is latent in the data, having a practical, artistic, or scientific purpose.” This further broadens the scope of sonification by including a variety of goals that reflect the intrinsic interdisciplinary and multidisciplinary nature of the field [21, 22].

The authors here propose two illustrations of the discussion above. The first, Fig. 1, is a visualization of the semantic analysis conducted on specific keywords (e.g., “data,” “communicative intention,” “listening”) within the sonification definitions discussed above, to identify their relative impact and evolution over time. It explicates how the historical definitions of data sonification oscillate between two poles: one that sees data as objective entities whose properties are systematically mapped to specific acoustic parameters and one that emphasizes the communicative intention of the designer and the central role of the audience in building knowledge through listening.

The second, Fig. 2, situates sonification within a network of related concepts, as generated by Sealsology, a web application that allows the visual exploration of the semantic area related to any Wikipedia Page [23]. It shows how the search entry “sonification” is positioned, indirectly, as a sort of middle ground between “sound art” and “music computing” while having direct links to “scientific visualization” and “acoustics” (and to more obscure entries such as “Transmission Arts” and “Emily Howell,” the name of David Cope’s AI-inspired composition system). The concept graph can be seen as an indicator, albeit imprecise, of

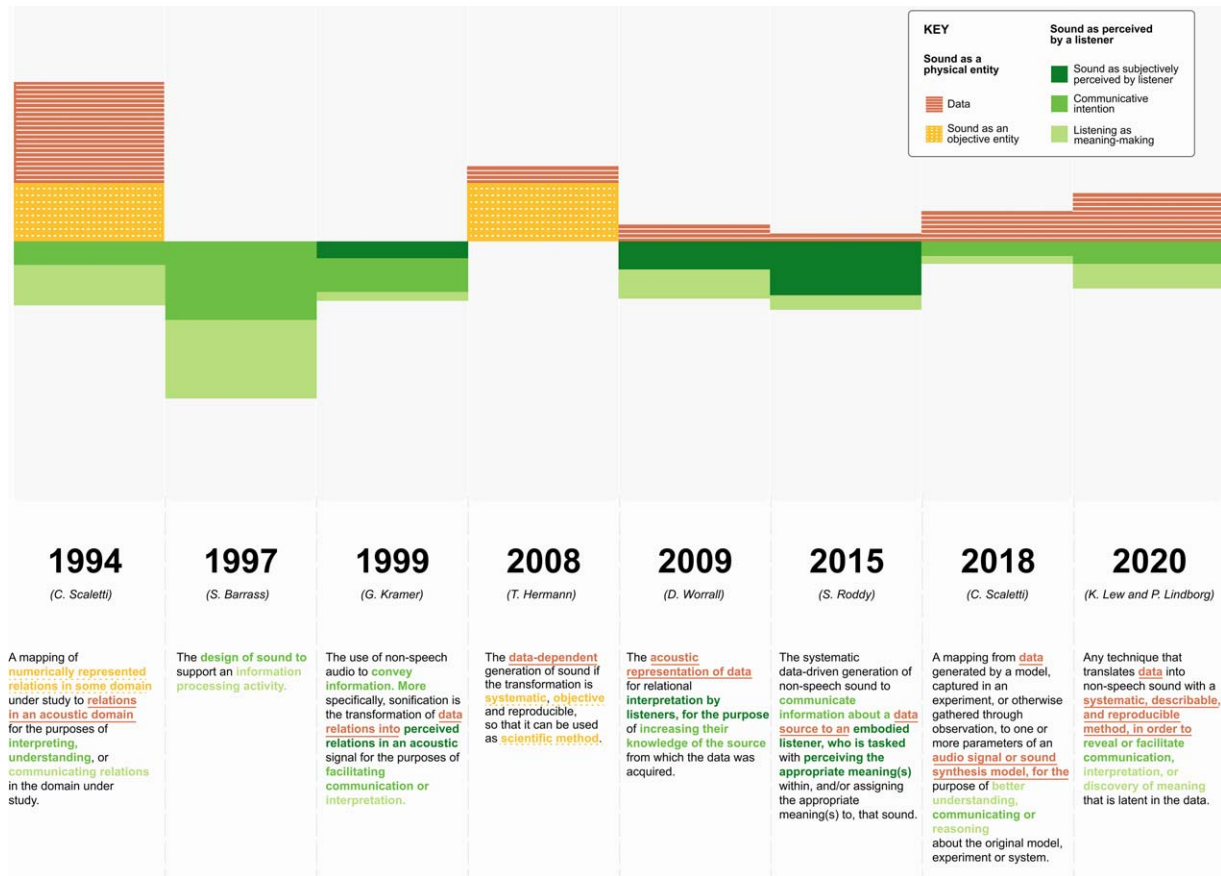


Fig. 1. Visualization of the results from the semantic analysis of “sonification” definitions. Warm colors (brown and yellow, upper part of the illustration) signify terms within the definition of the concept of “sound as an objective entity.” Conversely, cooler tones (shades of green, lower part of the illustration) represent “sound as perceived by a listener.” The gray area corresponds to the entirety of the definition, and the size of colored blocks is proportionate to the number of words in the sentence.

the tension between “hard science” (or utilitarianism) and “humanism” (or hedonism): a dichotomy that is also found in the definitions of data sonification within the academic community.

By presenting a comparative analysis of classification strategies of the Data Sonification Archive (DSA), this study aims first and foremost to contribute to the discussion about this tension, which is inherent in the field’s self-understanding of what sonification is. As the field moves toward maturity, it is critical for the community to map (and acknowledge) the diversity of goals, users, and design strategies of data sonification projects, toward a richer approach to human-data relationships.

## 0.1 The Data Sonification Archive

In this paper, the authors report on classification strategies for the DSA, a crowd-sourced web platform that collects and categorizes sonification projects. The wide range of projects illustrate that the field of sonification has a firm basis in engineering and science and that it evolves together with sound art and music computing. Indeed, sonification as a field manifests a multiplicity of goals, design methods, and intended audiences.

The archive was conceived and launched in early 2021. Curated by two of the present authors (Lenzi, Ciuccarelli, and from autumn 2023, joined by Lindborg), it receives its material directly from authors—researchers, composers, and technologists—in the community. The DSA is intended as a collaborative effort to chart the territory of the rapidly growing field of sonification and explore how it is evolving. First and foremost, the DSA facilitates a deeper understanding about sonification projects: when and where it is used (the context), how (what real-world phenomena it describes), why (purpose), and for whom (end users, e.g., audiences). Largely inspired by the Data Physicalization Archive [24], the authors imagined the DSA as an aggregator of the broader sonification community beyond academic research and an opportunity to collect open, reusable data to further analyze the design strategies, mapping metaphors, and evaluation protocols currently used in sonification. As such, the present authors see the DSA as part of the ongoing effort toward a standardization of design methods, tools, and evaluation protocols for sonification [22, 25, 26].

At the inception of the DSA, a first group of around 50 use cases for sonification was assembled by two of the authors of this paper. The use cases served as material for a series of workshops dedicated to the definition of a design tool, the Sonification Canvas [27], ideated to guide designers in

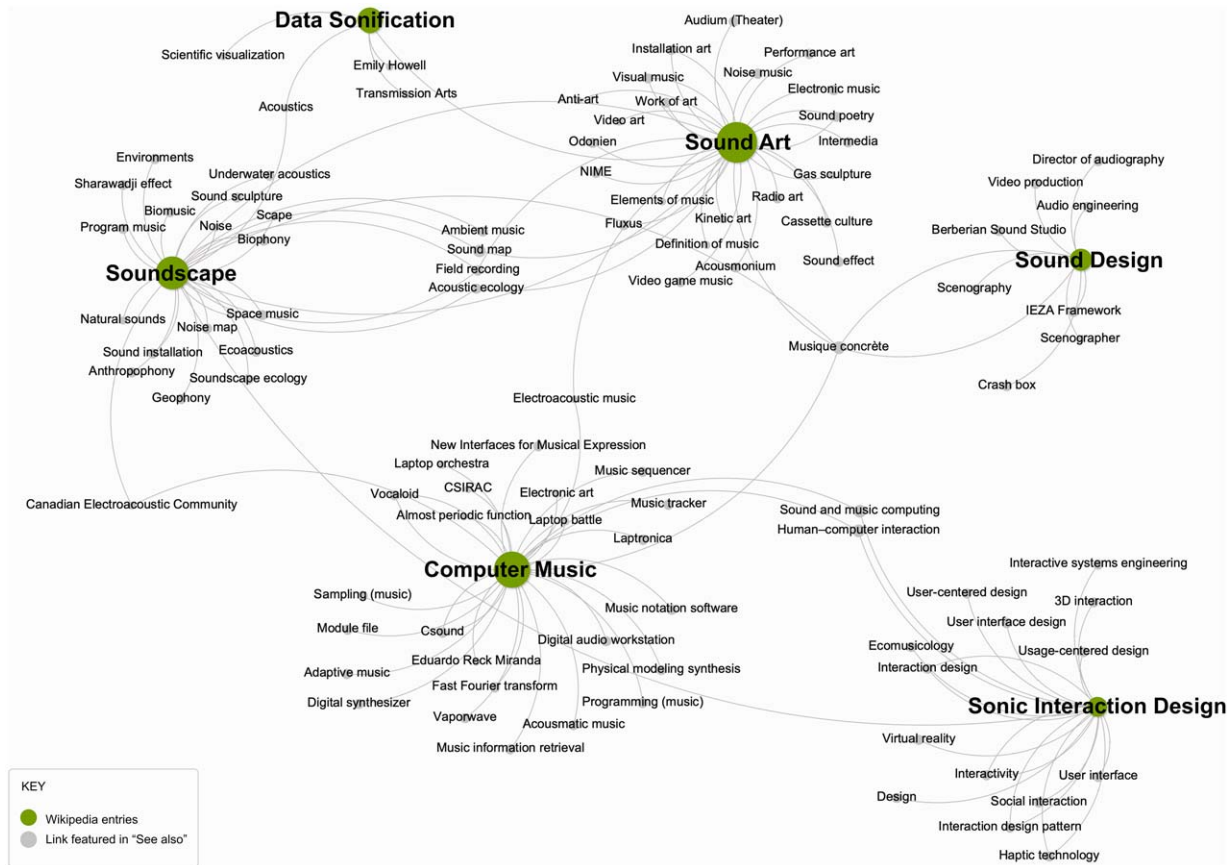


Fig. 2. Sealsology map of Wikipedia entries related to “Sonification,” “Sound Art,” “Soundscape,” “Sound Design,” “Computer Music,” and “Sonic Interaction Design,” represented as green nodes. The links between the Wikipedia entries as features in “See also” (in the related Wikipedia page) are in gray.

using sound for data representation. The Canvas’s boxes, which prompt authors of sonification to reflect on their design process and choices, were iteratively defined through interviews with sonification experts and workshops with information designers. In a first series of workshops, participants were asked to classify existing sonification projects by identifying the topic (i.e., the phenomenon described by the dataset used in the project), type of end user (e.g., general public, expert user), and intended goal of the sonification (i.e., education, accessibility, data analysis, and so on). These are familiar categories in information and communication design, where the definition of the use case is considered a preliminary step that follows a typical design thinking process. During the workshops, other cases were added to the available set, and other characteristics were suggested to further classify the cases. Specifically, participants suggested that the description of the different sensory modalities involved in the sonification project (i.e., the “media mix,” see further below) and the sonification method (e.g., audification, Parameter Mapping, model sonification) would be included as relevant characteristics.

**0.2 Related Work**

To capitalize on this first set of sonification projects and the proposed classification, the curators created a repository that was publicly launched as an online collection in

January 2021. Currently, in addition to manual upload by the curators of the DSA, new projects can also be submitted by the public through an online form. On submission, a working web link to the sonification, the name of the authors and year of release, together with a short description of the work and a contact email are required. To be included in the DSA, a sonification project must be accessible online [i.e., the sonification (or examples of it) can be listened to].

The Sonification Art blog [27], an archive in the form of a weblog with detailed reports and interviews to authors of sonification, which focuses only on sonification “in an artistic context,” merged into DSA in 2021. ICAD, mentioned previously, is another source for sonification projects that could be explored in future endeavors. However, papers published in the ICAD archive do not necessarily include multimedia content or provide direct access to the sonification, which is problematic for a study aiming at understanding and classifying vital aspects of projects, such as the sounding output (cf. [16]). Moreover, since authors need to participate at a conference before they can publish their work in the proceedings, there is a barrier to entry. This suggests that the ICAD repository might not capture the current state of the large field of data sonification and, in particular, might be missing out on approaches that are evolving independently of academia.

The DSA project has to be read in the context of the evolution of the field of sonification over the past two decades.

As described in SEC. 0, while the field has started within the framework of scientific research with authors of sonification projects mainly coming from a computer music background [28], over the years, examples of sonification have greatly diversified to include artwork by authors who describe themselves as artists, composers, and sound or visual designers and a wide range of projects that can be described as design-driven [29] (i.e., conceptualized and implemented with the intention to solve a specific need or problem of a specific user). This approach would include projects that aim at developing real-world applications such as, for instance, real-time monitoring [30], education [31], and accessibility [32]. Furthermore, “data journalism” has recently been added to the pool as an area where sonification is increasingly embraced as a resource to improve the communication of complex datasets to nonspecialized audiences, especially in the context of podcasts and radio [33].

This increased variety of usages of sonification is reflected in a growing debate, especially within the auditory display community, around topics such as the role of aesthetics [14, 20, 18]; the need for shared design processes, methods, and tools [22, 27, 29, 34–36]; the urgency of establishing rigorous criteria for evaluating the impact of sonification projects [37]; and development of the relationship between the data sonification and visualization communities [38, 39]. Notably, in recent years, a clear interest from professional designers in integrating sonification techniques to better represent and communicate data to a non-specialized audience has also emerged and is on the rise [40–42]. In this context, a thorough analysis of the current sonification landscape would be an important milestone to assess the who, why, and how of sonification, and its impact beyond academia. Conversely, such insights could stimulate a collective reflection and provide critical knowledge for the advancement of the field toward a shared sonification design theory and the adoption of sonification as a widely accepted medium for improved human-data communication.

### 0.3 Aims of the Study

The present study represents the next phase in a line of inquiry into sonification projects that aims at describing their intended and perceived characteristics, sonic and visual media forms, and strategies for classifying them. Several recently published sonification analyses have focused on specific subsets of the DSA. For example, Zanella and collaborators [43] reviewed nearly 100 astronomical sonification projects stored in the DSA, including sonifications for accessibility in research and education, and software applications developed specifically to sonify astronomical data. Their goal was to assess the state of the field of sonification for astronomical research as well as to identify potentials, limitations, and provide future directions to widen the adoption of sonification in the astronomy community.

Caiola and collaborators [38, 44] developed a theoretical framework to map the overlapping between sonification and visualization design principles, largely basing the work

on the DSA. Lindborg and collaborators analyzed topics, qualitative characteristics, and perceived aesthetics in 32 projects that target climate data [45]. In this meta-study, two-thirds of the corpus was gathered from the DSA and one-third from the proceedings of the 2022 Data Art for Climate Action (DACA) conference [46]. Other studies have systematically analyzed and classified sonification projects to provide design guidelines and/or contribute to the standardization of data-to-mapping strategies are limited albeit influential [16, 17, 47].

In addition to the above, the Archive has been presented at the AudioVisual Analytics Community Meetup [48], IEEE VIS 2022 Application Spotlight [49], and Information+ [50] with a specific focus on projects that combine sonification with data visualization, a growing field of study as confirmed by the recent state-of-the-art report by Enge and collaborators [51]. Lenzi and Ciuccarelli [48] presented work on COVID-19–related sonification projects—an emerging trend in the DSA during the lockdown period—at the Outlier conference in 2022 [48]. The presentation aimed at engaging the broader information design community in a conversation on the potential of integrating other sensory modalities into data visualizations.

This paper presents the results of the first comprehensive analysis of the classification strategies and the resulting emerging categories of the 445 projects currently included in the DSA. Through this study, the authors aim at providing the sonification community with insights into where, how, and why sonification is currently used, with particular attention given to how sonification is combined with other data representation strategies, notably visualization.

## 1 ANALYSIS

### 1.1 Corpus, Methods

The present study is the first that takes a global perspective of the entire DSA, as it currently stands. A total of 445 projects published on the DSA website (by August 1, 2023) were included. The DSA datafile is available in **Supplementary Materials 1**.<sup>1</sup> In what follows, the authors focus on six curatorial classifications and explore the merits of computational classification methods based on text and audio that might be used for predictive modeling.

Hierarchical classifications can be defined in a top-down way (typology) or bottom-up (taxonomy, i.e., emergent). The DSA has grown organically using both approaches. Once the accessibility of the submission was confirmed, the DSA curatorial team made a heuristic classification of each case according to the principles explicated below. See Fig. 3 for an overview of curatorial classifications and their subdivisions.

### 1.2 Curatorial Classifications

Over the course of the first two years of the DSA, the curators of the project have iteratively defined a classifica-

<sup>1</sup><https://github.com/SonoSofisms/ears-eyes/blob/main/SupMat1-Metadata-Sonification-Archive.xlsx>.

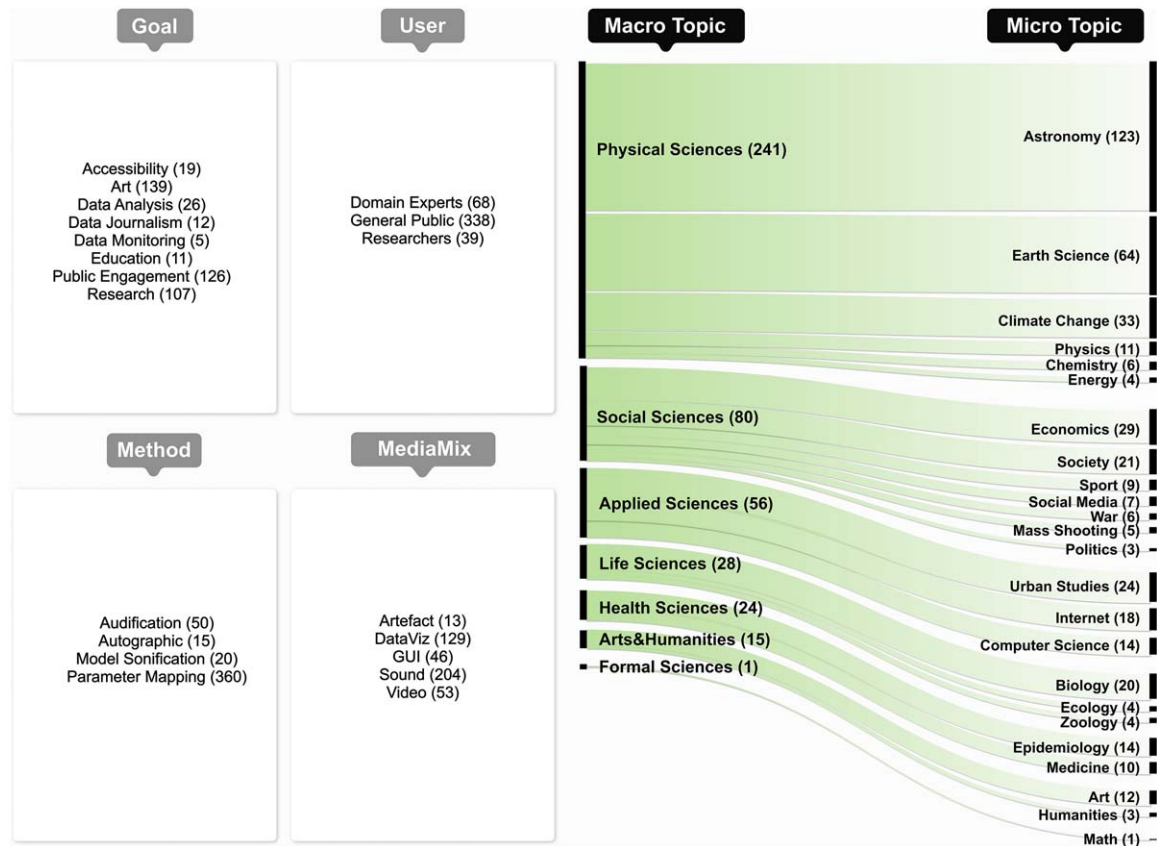


Fig. 3. Overview of the curatorial classification's architecture, with six *macro* category, each with their corresponding *micro* categories. In parentheses is the number of cases for each group. The visualization highlights the correlations between *Macro Topic* and *Micro Topic*, revealing unique correspondences between the two categories. The specific categories within the fields *Goal*, *User*, *Method*, and *MediaMix* are also reported, along with the number of cases for each category.

tion system for the submitted projects based on macro-categories (e.g., topics, purpose, and users; see further below). Progressively, related sub-categories (or micro-categories) were identified whenever needed or when a growing number of cases in a macro category shared similar characteristics. For instance, the topic “physical sciences” rapidly expanded to 198 cases, which led to introducing subdivisions, such as earth sciences, astronomy, biology, chemistry, physics, and so on. This top-down process is iterative: Categories are added, withdrawn, or refined, as required by the organic growth of the DSA. Classification of each new sonification case in the various categories is heuristically driven by closely observing the accessible documentation, which includes the sonification itself, any concurrent data visualization, other visual content (e.g., videos or static images providing contextual information), descriptions provided by the authors (mainly textual, but sometimes with graphics, physical media, software demos etc.), related academic publications, reception by audiences and media (e.g., reviews), and so forth.

As such, the curatorial decisions about how to classify cases in the DSA have since the start been driven by “observable and systematic characteristics attributed to the phenomena. This process can be automatic, if computational classifiers are available, or manual, when they are not, or when the taxonomy is relatively small. In the

latter case, hyponyms [sub-categories] can be identified by careful semantic interpretation constrained by contextual factors” [52]. Such an interpretation often relies on tacit knowledge; in other words, decisions can be based on “ideas and information on which we draw without necessarily realising that we do so” [53]. While tacit knowledge does reflect “the larger body of distributed knowledge embedded in social memory and collective work practice” [53], it must be made explicit in order to contribute to theory.

To this end, in this study, the authors investigate how the curatorial categorizations of the DSA correlate with automatic classifications of the same sonification cases, by means of unsupervised analysis of textual descriptions and sonification audio. Conversely, similarities and differences emerging from comparing classification strategies will help us explicate the curatorial choices and reflect upon a new theory of sonification.

The goal with this line of inquiry is not to replace the curatorial decisions but to develop a predictive model that supports the DSA curators' decisions. The model should take the project's media materials (e.g., an excerpt from the sonification) and textual descriptions as inputs and suggest how the project might be classified in different categories. A brief description of the categories used for the curated classification of the DSA follows.

### 1.2.1 Goal, User

The classifications into *Goal* and *User*, familiar to designers, are commonly used to highlight the constraints, opportunities, and intended message of a project [54]. In the DSA, they respectively identify the purpose of the sonification (such as Public Engagement or Monitoring) and its final recipients, as intended by the author (e.g., General Public or Researcher). The reader can refer to Fig. 3 for the full list of *Goals* and *Users*.

### 1.2.2 Macro Topics, Micro Topics

The Macro and Micro levels of topics are directly connected. They classify either areas of knowledge or physical phenomena that the sonified data refer to. The distinction by two levels corresponds to “data provenance” and “subtopics” in our previous work (compare with Fig. 1 in [45]). In the present work, the categories for topics in the taxonomy are borrowed from the classical canon that defines the branches of human knowledge, distinguishing seven Macro categories (such as Physical Sciences or Arts & Humanities) and 24 Micro subdivisions (such as Astronomy, Economics, or Urban Studies). See Fig. 3.

### 1.2.3 Method

The term “method” used in this context is well described in the sonification community; from there, the authors include categories for Audification, Parameter Mapping, and Model Sonification [55]. Emerging from more recent projects of relevance to the DSA and inspired by visualization design research [56], the authors are adding a fourth and new category, Autographic, which will be defined in SEC. 3.

### 1.2.4 MediaMix

The classification *MediaMix* is intended to further specify the context in which a sonification is experienced and, specifically, which combination of media is used to engage the listener. Projects are categorized as Sound when only sonification is presented (e.g., as an audio file on an online player or as a live performance); DataViz if the sonification is coupled with a visualization of data that refer to the same phenomenon (29% of projects in the corpus); Video whenever moving images are added to the sonification (e.g., to provide contextual information for the sonification or add a narrative/artistic expression); GUI when the project includes a visual (graphic) interface through which the listener “plays,” generates, or customizes the sonification (e.g., by setting audio parameters, adjusting the output, uploading sound files, etc.); and finally, Artefact to index sonifications that are generated by interacting with a physical object.

### 1.2.5 Analysis of Curatorial Classifications

Given the classifications above, the authors consider which ones are actually used in the DSA. There are 11,520 combinations ( $8 \times 3 \times 24 \times 4 \times 5$ ; note that the seven categories in *Macro Topic* are fully defined by the respective project’s *Micro Topic*, so that they would be redundant

to include). Out of these, 232 different combinations are used for the 445 projects. The most common one, shared by 21 projects, is defined as *Goal* = Public Engagement, *User* = General Public, *Macro Topic* = Physical Sciences, *Micro Topic* = Astronomy, *Method* = Parameter Mapping, and *MediaMix* = DataViz.

See Table 1 for a list of combinations shared by five projects or more and Fig. 4, which displays 232 perfect matches (in gray), emphasizing the first six, indicating a greater involvement in numerous projects (depicted in different shades of gray). In these top six matches, detectable trends include Art and Public Engagement as common *Goals*, General Public as the preferred *User* base, and *Topics* such as Astronomy, Climate Change, and Earth Science (all under Physical Science). Parameter Mapping emerges as the preferred *Method*, accompanied by a diverse *MediaMix* including DataViz, Sound, and Video.

## 1.3 Computational Classifications

### 1.3.1 Audio

1.3.1.1 Materials. Audio files of sonifications could be extracted from 354 out of the 445 projects. Many projects had published output materials in the form of audiovisual files in a range of formats and styles (i.e., movies on Vimeo, YouTube, etc., with or without other media materials such as voice-over explanations). Most audio files were in high-quality mp3 format, which the authors deemed sufficient for the purposes of this analysis. After extraction, all files were listened to by the researchers in order to assess that the audio did not contain overly long silences before or after the actual piece and that quality was adequate. In line with the original definition of sonification, especially limiting to “nonspeech audio,” any voice-over narration that was clearly not data-driven (i.e., speech superimposed onto the actual sonification) was eliminated. The audio files were then batch preprocessed by applying fade-in and fade-out (0.02 s; this avoids clicks), resampling to 16-bits depth and 44,100-Hz sample rate, normalizing by RMS power to  $-18$  dBFS (joint channels), converting to stereo (a small number of projects used mono output), and exporting as mp3 at a constant rate of 192 kbps. The DSA audio corpus is 1.25 GB and available for research purposes upon request. The mean duration of audio files was 2 min 27 s, and the median was 1 min 32 s, all in a range from 2 s to 20 min.

1.3.1.2 Descriptors. Since the dataset had 354 projects with audio, and the “one in ten” rule-of-thumb in statistics can mitigate against overfit in predictive modeling, the authors decided to employ no more than 35 descriptors in the analysis. They started by identifying ten low-level and mid-level computational features that are commonly used in music information retrieval (MIR) [18, 57, 58]. From the seewave package (version 2.2.0) [59] running in R, the authors extracted RMS, Spectral Centroid, Spectral Flatness, and Shannon Entropy. From the MIR Toolbox (version 1.8) [60] running in MATLAB, they extracted Spectral Brightness (mirbrightness), zerocross rate (mirzerocross), Spectral Rolloff (mirrolloff, at 85%), Spectral Spread (mir-

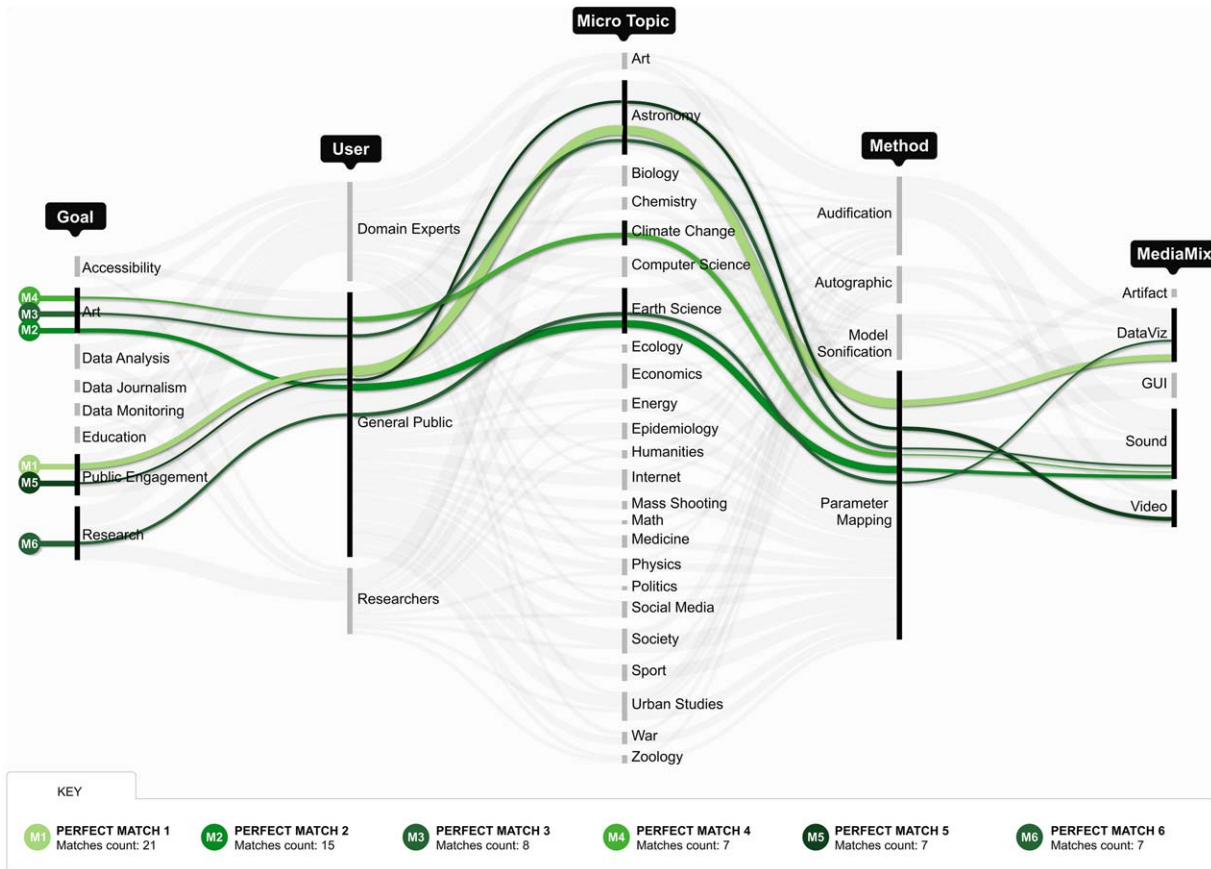


Fig. 4. Sankey diagram of 232 perfect matches among six curatorial classifications in the archive.

spread), and Spectral Entropy (mirentropy). Finally, they defined an operational descriptor for panning, Channel Difference, by taking the difference in RMS between left and right channels. The rationale for including panning was that spatiality has been shown to be an important parameter for sonification [47] and that almost all audio files in the dataset were in stereo.

The ten features were extracted in nonoverlapping time frames of 0.5 s, creating a set of multivariate time series. Three statistics were then obtained to describe each time series: the mean, standard deviation, and slope (i.e., linear regression trend). Different sizes for time frame or window overlap did not significantly alter the results. This yielded a total of 30 audio descriptors per project, plus duration. For an overview, see Table 2. Note that for the panning descriptor Channel Difference, it can be said that a high difference in a single frame would indicate a higher intensity in one channel, a high absolute mean across frames would mean an unbalanced or “tilted” stereo image, a high standard deviation would indicate variation in the stereo image width, and a high (steep) slope might indicate an overall significant movement of sounds across the panoramic image.

Many of the audio descriptors (aka MIR features) displayed a non-normal distribution. They were preprocessed by applying a power transformation using a Box-Cox method in the AID package [61, 62] and trimming at  $\pm 3$  standard deviations, which significantly improved the clustering results. As a side note, the authors also explored

principal component and factor analysis for dimensionality reduction prior to clustering, but here the improvements did not warrant the increased analytic complexity. Therefore, the following analysis was conducted on the full set of 30 variables, after power transformation and gentle trimming of outliers.

1.3.1.3 Cluster analysis. The authors explored several different algorithms for unsupervised centroid-based or hierarchical-based clustering. Results from the following eight algorithms are reported: kmeans (k-means clustering) and hclust (agglomerative hierarchical clustering) included in the standard distribution of R [63]; KMeans\_arma (k-means using Armadillo), KMeans\_rcpp (k-means using RcppArmadillo), Cluster\_Medoids [partitioning around medoids (PAM)], and Gaussian Mixture Model (GMM) from the ClusterR package [63, 64]; *fastkmed* from the kmed package [64, 65]; and *pam* (PAM) from the fastkmedoids package [66, 67]. The number of clusters in each solution was requested to match the number of categories the curatorial classifications, i.e., *Goal*, *User*, *Macro Topic*, *Micro Topic*, *Method*, and *MediaMix*, respectively. This allowed, in the next step, to measure the association between the automatic (i.e., computational) and curatorial clustering.

### 1.3.2 Text

1.3.2.1 Materials. Descriptive texts could be manually extracted for 436 out of the 445 sonification projects, fol-

Table 1. The 15 most common curatorial classifications in the dataset, with IDs for the projects.

Goal	User	Macro Topic	Micro Topic	Method	MediaMix	Count	Project IDs
Public Engagement	General Public	Physical Sciences	Astronomy	Parameter Mapping	DataViz	21	5, 6, 58, 82, 115, 127, 141, 145, 150, 212, 225, 245, 267, 323, 341, 367, 372, 384, 397, 410, 412
Art	General Public	Physical Sciences	Earth Science	Parameter Mapping	Sound	15	38, 63, 68, 116, 129, 132, 135, 178, 194, 219, 241, 263, 269, 348, 398
Art	General Public	Physical Sciences	Astronomy	Parameter Mapping	Sound	8	24, 39, 70, 197, 316, 363, 378, 406
Art	General Public	Physical Sciences	Climate Change	Parameter Mapping	Sound	7	160, 165, 193, 198, 231, 411, 439
Public Engagement	General Public	Physical Sciences	Astronomy	Parameter Mapping	Video	7	11, 95, 171, 213, 221, 308, 336
Research	General Public	Physical Sciences	Earth Science	Parameter Mapping	DataViz	7	151, 158, 159, 201, 289, 377, 443
Art	General Public	Life Sciences	Biology	Parameter Mapping	Sound	6	106, 185, 232, 271, 385, 395
Public Engagement	General Public	Physical Sciences	Climate Change	Parameter Mapping	DataViz	6	47, 238, 244, 320, 321, 396
Public Engagement	General Public	Physical Sciences	Climate Change	Parameter Mapping	Sound	6	16, 230, 243, 302, 361, 374
Public Engagement	General Public	Physical Sciences	Astronomy	Parameter Mapping	Sound	6	17, 19, 25, 30, 183, 431
Art	General Public	Physical Sciences	Earth Science	Audification	Sound	5	92, 122, 143, 252, 444
Art	General Public	Physical Sciences	Astronomy	Parameter Mapping	Video	5	170, 216, 293, 294, 337
Art	General Public	Physical Sciences	Economics	Parameter Mapping	Sound	5	103, 138, 195, 247, 278
Public Engagement	General Public	Physical Sciences	Astronomy	Parameter Mapping	GUI	5	173, 237, 246, 265, 409
Research	Domain Experts	Physical Sciences	Astronomy	Audification	Video	5	23, 37, 112, 286, 329

Table 2. Overview of audio descriptors for 354 sonifications.

Quantile	Duration	RMS_m	Chdiff_m	Cent_m	Flat_m	Shannon_m	Brightness_m	Zerocross_m	Rolloff_m	Spectspread_m	Spectentropy_m
25%	51.6	0.0132	-0.000613	1110	0.0355	0.632	0.17	414	1760	1770	0.648
50%	92.3	0.019	2.22E-11	1660	0.0563	0.698	0.266	677	2870	2290	0.711
75%	190	0.0312	0.000935	2410	0.0874	0.765	0.421	1070	4870	2930	0.777
		RMS_sd	Chdiff_sd	Cent_sd	Flat_sd	Shannon_sd	Brightness_sd	Zerocross_sd	Rolloff_sd	Spectspread_sd	Spectentropy_sd
25%		0.00642	0.000447	372	0.0223	0.0401	0.0612	158	689	342	0.0348
50%		0.00873	0.00323	731	0.0421	0.0596	0.103	321	1330	501	0.051
75%		0.0133	0.00737	1190	0.0775	0.0856	0.163	569	2160	701	0.072
		RMS_k	Chdiff_k	Cent_k	Flat_k	Shannon_k	Brightness_k	Zerocross_k	Rolloff_k	Spectspread_k	Spectentropy_k
25%		-2.27E-05	-6.97E-06	-1.6	-9.82E-05	-0.000109	-0.00019	-0.545	-2.46	-1.8	-0.000115
50%		5.56E-06	-5.46E-14	0.216	-1.25E-06	2.58E-05	3.16E-05	0.241	0.187	0.0448	1.92E-05
75%		4.58E-05	2.35E-06	2.48	9.51E-05	0.000306	0.000386	1.79	4.44	1.6	0.000248

lowing the team's previously developed procedure [45]. The mean number of words was 300 per project, with interquartile limits at 107 and 347 words; the longest description had 2,174 words. In total, the text descriptions contained 133,622 words. About 31% were nouns and 16% were verbs. The most common nouns, appearing at least 100 times, were as follows: data (3.23%), sound (1.43%), sonification (1.37%), time (0.83%), music (0.79%), project (0.62%), information (0.42%), years (0.39%), song (0.38%), notes (0.36%), system (0.34%), way (0.33%), part (0.32%), composition (0.31%), piece (0.31%), work (0.29%), people (0.29%), space (0.29%), climate (0.28%), stars (0.27%), note (0.27%), image (0.26%), pitch (0.26%), year (0.25%), number (0.25%), and installation (0.24%).

1.3.2.2 Topic modeling. For the computational classification of texts, the authors employed Latent Dirichlet Allocation (LDA) [68]. It is a modeling technique that uses unsupervised machine learning to determine terms (i.e., word stems) that separate a text corpus into topics [69]. It ignores syntactic information and treats the corpus as a bag of words, specifically, unigrams. The basic idea is that every text in a corpus can be represented as a random mixture over latent topics, each characterized by a distribution over terms. The authors conducted the analysis using the `topicmodels` package [32] in R. Using this package, the core functions can be tuned in several ways. In the present case, the authors followed recommendations by Grün [72] regarding the definition of the document-term matrix, by removing stop words, numerals, and punctuation; excluding words shorter than three characters; stemming; and keeping only matrix items whose number of nonempty terms were more than 1% of all terms. Similarly to the MIR-based clustering of audio descriptors, specific LDA solutions were generated with sizes to match the respective curatorial classifications. See **Supplementary Materials 3<sup>2</sup>** for examples.

## 2 RESULTS

### 2.1 Correlations Between Classifications

The association between curatorial and computational classifications in the DSA data was analyzed. To estimate the correlation between two nominal variables, Pearson's  $\chi^2$  statistic can be used, because it is based on observed and expected frequencies in a contingency table of the counts of the two variables' categories. The strength of this relationship is indicated by Cramér's V coefficient [73]. In the present dataset, pairwise comparisons were made between vectors of nominal (i.e., unordered items). For example, the curatorial classification *Goal*, having eight categories, was compared against each of the different clusterings of audio data based on MIR features, requesting eight clusters to be found, and against a text clustering based on an LDA model with eight topics. The curatorial classification of *User*, with

its three categories, was compared against audio-based and text-based clusterings with the same size of three.

As can be seen in Table 3, the association between LDA clustering (automatic classification of text) was strong for all six curatorial classifications, with Cramér's V ranging from 0.178 for *MediaMix* to 0.418 for *Micro Topic*. The fact that it was much stronger for *Micro Topic* might be explained by considering that the project texts tended to focus on the data source, i.e., point toward the phenomenon that the sonification aimed at showcasing, rather than spending ink on describing the combination of media that was used, the *MediaMix*, which might have been considered as self-explanatory. Meanwhile, the association between any of the MIR-based clustering (automatic classification of audio) against the six curatorial classifications was generally weaker. All eight audio-based clustering methods were clearly significant for *MediaMix*, which confirms the intuition that audio features would differ across its categories, thus reflecting different compositional and design choices of the authors when dealing with only sound or with sound combined with, for instance, static or moving images. Some methods did well for *Micro Topic*, while for other curatorial classifications, the associations were very weak or nonsignificant. Overall, the *KMeans\_rcpp* clustering method produced significantly strong association with the largest number of the curatorial classifications, except for *Micro Topics* and *Macro Topics*.

There could be different reasons for the observed discrepancy in strength of association between text-based and audio-based automatic classifications. Firstly, text-based topic modeling might simply be a stronger method than the audio-based clustering methods that were tested. Note that this reasoning has little, if anything, to do with the content of the curatorial classifications or how they were made. Secondly, the authors' intentions were more clearly articulated by them in writing than what it was in their composing of an "audio piece" with sonification techniques. Thirdly, the curators might have prioritized the projects' textual descriptions more than the actual sound of the sonifications, and therefore, the curatorial classifications were more aligned with the former.

### 2.2 Predictive Modeling

The authors explored prediction modeling of curatorial classifications from text and audio classifications using the `nnet` package [70], which implements a feed-forward neural net architecture. The analysis was restricted to the subset of DSA that had complete text and audio, i.e., both LDA-based and MIR-based classifications, for a total of 351 projects. Several network configurations were tested. In most cases, the most parsimonious solution had an input layer to encode two computational classifications; the hidden layer was chosen to have a size comparable to the number of categories in the target curatorial classification; and the output would have the same number of nodes as the target. The Akaike information criterion was consulted to decide which computational classifications to include in modeling. The

<sup>2</sup><https://github.com/SonoSofisms/ears-eyes/blob/main/SupMat3-DSA445-text-LDA.xlsx>.

Table 3. Associations between automatic clusterings of audio (eight algorithms) and text and six curatorial classifications. Numbers in parenthesis for the latter indicate the number of categories and clusters. Cells show Cramér’s Fischer-adjusted V with associated p values calculated with Fischer’s exact method. By convention, the number of asterisks indicates the degree of significance, so that \*\*\* = very strong correlation (p < 0.001); \*\* = strong (p < 0.01); and \* = significant (p < 0.05). Since ordinary kmeans and LDA are sensitive to the initial random selection of starting points, the table gives median values of multiple assays (i.e., across 500 iterations for kmeans and 100 iterations for LDA).

Data	R package	Algorithm	Curatorial classifications					
			Goal (8)	User (3)	Macro Topic (7)	Micro Topic (24)	Method (4)	MediaMix (5)
Audio	stats	kmeans	0.145, p = 0.23	0.084, p = 0.27	0.132, p = 0.15	0.258, p = 0.081	0.126, p = 0.061	0.158, p = 0.0018**
		hclust	0.136, p = 0.38	0.102, p = 0.084	0.105, p = 0.66	0.237, p = 0.64	0.088, p = 0.44	0.176, p = 0.0013**
	ClusterR	KMeans_arma	0.169, p = 0.015*	0.054, p = 0.75	0.123, p = 0.32	0.263, p = 0.2	0.117, p = 0.12	0.161, p = 0.0024**
		KMeans_rcpp	0.159, p = 0.0093**	0.115, p = 0.048*	0.127, p = 0.14	0.260, p = 0.46	0.135, p = 0.028*	0.162, p = 0.00064***
		Cluster_Medoids	0.156, p = 0.023*	0.082, p = 0.31	0.115, p = 0.53	0.270, p = 0.0045**	0.119, p = 0.15	0.156, p = 0.0036**
Text	fastkmed	0.155, p = 0.012*	0.097, p = 0.15	0.133, p = 0.18	0.272, p = 0.046*	0.111, p = 0.17	0.166, p = 0.0022**	
	fastkmedois	0.159, p = 0.18	0.095, p = 0.17	0.122, p = 0.3	0.248, p = 0.057	0.109, p = 0.25	0.149, p = 0.016*	
	topicmodels	0.156, p = 0.022*	0.082, p = 0.3	0.115, p = 0.53	0.271, p = 0.0019**	0.119, p = 0.15	0.156, p = 0.004**	
	LDA	0.241, p = 1.7e-16***	0.227, p = 4.3e-05***	0.245, p = 3.6e-15***	0.418, p = 2.1e-41***	0.276, p = 3.6e-12***	0.178, p = 0.0015**	

criterion follows closely the V statistic used previously, and therefore, it is reported in Table 3.

For all six models (one per curatorial classification), the LDA text-based classification contributed more information to explaining the target; and most often, the best audio-based clustering method was KMeans\_rcpp. In each call to the nnet() function, the dataset was split with a three-quarter sample used for training against true values (the target curatorial classification), and the remaining one quarter was used for testing. As before, the output prediction was evaluated with Cramér’s V (with Fischer adjustment) and significance level given by Fischer’s exact test. The data split was then resampled, and the process repeated 500 times, for each of the six targets. The median value for association strength and significance indicate the performance of the model in each case.

Predictions of *Goal* were reasonably well balanced among seven out of the eight categories. Median Cramér’s V was 0.339 (p = 0.080), with 95% confidence limits of 0.239 and 0.486.

For *Method*, predictions were heavily weighted (81%) to one category, apparently corresponding to the dominant Parameter Mapping category (83%). The discrepancy in size of the categories might have made modeling more difficult. Still, median V was 0.328 (p = 0.080), with confidence limits at 0.058 and 0.571.

The prediction model for *User* failed outright with the same two predictors as above, for reasons the authors were unable to pin down. Including or replacing with the second-best audio clustering method, GMM, yielded an unbalanced and weak model, median V = 0.058.

For *Macro Topic*, the two predictors highest in information were LDA and ordinary kmeans (rather than KMeans\_rcpp), with median V = 0.279 (p = 0.075) and confidence limits at 0.183 and 0.418. The model for *Micro Topic* failed to produce an output, probably because the number of categories was too large and/or the number of examples too small for this network to handle.

Finally, the *MediaMix* model with LDA and KMeans\_rcpp as predictors was unbalanced, to some extent covering three of the five categories. However, median V was 0.308 (p = 0.21), with 95% confidence limits of 0.166 and 0.483.

### 2.3 Summary of Results

These results, while tentative, indicate a potential to employ automatic, computational classifications in support of the curatorial classifications. Three of the six, namely *Goal*, *Method*, and *Macro Topic*, might in the first place be suitable, while *User*, *Micro Topic*, and *MediaMix* would need further modeling work. Another way forward, to be undertaken in future research, would be to explore a reduction of the six curatorial classifications onto a lower-dimensional latent classification space, along the lines discussed above (see Section: 1.2.5 Analysis of Curatorial Classifications). This approach might yield a useful prediction model that is more closely tuned to the content and structure of the archive.

### 3 DISCUSSION

In an increasingly data-intense society, sonification research is gaining momentum as a complement to the visualization of data. Nonetheless, a series of unresolved issues are still preventing sonification's full transition from a niche practice for the presentation of scientific data to a widely adopted medium that can influence how complex phenomena is made sense of [71, 55, 10]. With diverse interests entering the field, the ingroup understanding of "sonification" is not coherent. While sonification was initially seen as a discipline closely associated with information engineering, with scientific evaluation criteria such as systematicity, objectivity, and replicability (cf. [2, 8, 6]), more recently, its closeness to electroacoustic composition has been emphasized [72, 71, 25]. For example, Goudarzi argued that "in interactive sonification, the sound creation task has sometimes been in the hand of technology developers but it has rarely gone beyond achieving aesthetically pleasing sounds (as opposed to annoying sounds!)... improvement of user experience in computer music languages has encouraged more sound artists to get more involved in the development process" [73]. Arguably, sonification has only recently started to move away from "a pre-theoretical stage" [22], and terminology might often mix terms from sound engineering, auditory perception, and music [6, 74, 75]. The techniques that practitioners employ might hail from engineering, coding, sound art, communication design, and music composition.

In comparison to the centuries-old intellectual history of data visualization [76], sonification is a baby. The authors believe that sonification, as a growing field of research not only seeking to define but also to renew itself, must gain a better understanding of information design in general and data visualization in particular. Therefore, in this study, the authors embarked on a multimodal analysis of the DSA and its multifaceted descriptions of projects, to critically discuss the classification strategies that the archive embodies to contribute to the ongoing discussion on the status of the field of sonification.

Since the inception of the DSA, the curators adopted a designerly approach to classification, borrowed from information and communication design [53, 54]. Through these lenses, the authors considered each sonification project as a response to the needs of a specific user, where the communicative intention of the authors (*Goal*) becomes tangible in an experience that uses a mix of different media to represent data pertaining to a specific topic.

Results from the analysis conducted in the current study show strong correlations between the curatorial classifications and automatic analyses of textual information provided by the authors of sonification projects, as well as to the audio content itself, albeit less strong. This result highlights how the need for introducing classifications and subdivisions that appear to go beyond what might traditionally be considered in sonification is consistent if sonification is looked at as a broader field. This analysis of the combinations of the six categories of the DSA curatorial classification highlights that the most common profile

is populated by projects that target a nonexpert audience (General Public) with the intent of engaging the listeners with the phenomenon represented (Public Engagement) through a Parameter Mapping sonification coupled with a data visualization of the same phenomenon. The cases in this group are all dedicated to the representation and communication of astronomical phenomena. This result raises interesting points that deserve further investigation.

First and foremost, the focus on a broader, nonspecialized audience seems to indicate that the field of sonification is now mature to transition from a niche scientific method toward a mass-medium for data communication, as it was advocated by Vickers and Barrass more than two decades ago (see [10, 25]). This shift will, in turn, increase even more the need for sonification designers to pay attention to the quality of the sonic experience of a listener who might not be familiar with consciously decoding information from sound. In this respect, the need for the sonification community to identify design guidelines that support a more successful (i.e., more efficient and engaging) meaning-making process is critical. Specifically, the role of Parameter Mapping as the main compositional strategy indicated that works, such as the recent analysis by Groß-Vogt and colleagues [16], that focus on providing a shared framework for efficient mapping metaphors, is extremely relevant for the field of sonification to advance.

Furthermore, the combination of data sonification with visualization in this group of projects is an indicator that multimodal representations of data, especially in the context of public communication, are powerful. In ongoing work, the authors are preparing a deeper investigation of a joint design framework for combined sonification and visualization. They observe that efforts from the community in this direction are increasing (see [38, 39, 44, 51]). Lastly, the predominance in this group of projects related to astronomy might be connected both to a specific interest of the astronomical community in sonification techniques [43] and to the recently established cross-disciplinary working group "The Audible Universe" [37], whose activities included the use of the Sonification Canvas [21] and, conversely, the submission of several projects of sonification for astronomy to the DSA.

#### 3.1 Four Perspectives for Classification Strategies

Therefore, the authors must return to the fundamental question: *What is sonification?* To set out a concluding framework to the present study, they will discuss aspects of the means and purposes of sonification. Both technique and style, sonification integrates aspects of 1) representation and exploration in the classic utilitarian and analytic-oriented way; 2) aesthetics, that is, the role of art, especially electroacoustic music composition and soundscape composition; 3) narration (as a mass-medium for communication); and finally, 4) intentionality (What purposes initiate and shape the creative dialogue between sonification-author and sonification-listener?). Is there a need, at this point in time,

for extending the very concept of “sonification”? Working with the DSA, the authors believe this is the case.

### 3.1.1 Representation and Exploration

Sonification has been defined as “any technique that translates data into non-speech sound with a systematic, describable, and reproducible method, in order to reveal or facilitate communication, interpretation, or discovery of meaning that is latent in the data, having a practical, artistic, or scientific purpose” [20]. Notably, this perspective includes aesthetics of sonification, enlarging on the “classic” engineering-oriented definition by Kramer [77], furthered by Hermann [8] and others. Data sonification is expanding from a practice used to conduct scientific analyses to a means of communication that broadens the range of languages and senses through which the general public makes sense of complexity in a data-intensive society.

Mapping the field of sonification through the DSA, a broad range of communicative intentions emerge: Sonification is used not only to analyze “hard data” driven by a specific task but also to explore complex events that are per se undefined and mutable. Sonification is also used to represent and communicate such complexity to a nonspecialized audience, with different purposes that range from the popularization of scientific research, advocacy, art, or even activism. Communicating to a wider audience, though, requires the author to intentionally shape a sonification so that it reaches the listeners, by taking their goals and the context in which they operate into consideration [29]. The analysis of the DSA heads toward *making explicit* the implicit decisions taken by authors of sonification during the design process. The authors believe that through this analysis, designers as a community can define shared design guidelines that help to expand the field’s impact and reach on society at large, while making sonifications overall more effective and engaging.

### 3.1.2 Aesthetics

There is an ongoing discussion in sound design and auditory perception research communities regarding the relationship between sonification and electroacoustic music composition, which this study contributes toward. It also suggests directions for the development of empirically founded design techniques that might be more effective in serving the communication needs of issues such as climate change, health, or political (mis)information, all of which are highly relevant for the nonexpert public and society at large [29]. As Barrass stated [25], design can provide the framework to expand sonification from a scientific analysis tool into an independent medium to enable meaning-making to take place in a context where sound coexists with other sensory modalities and data to nurture an interactive communication process with the user. “Usefulness and enjoyment” along with efficiency are the relevant parameters to “reconfigure sonification from an instrument solely for scientific enquiry into a mass medium for an audience with expectations of a functional and aesthetically satisfying experience” [25].

Vickers [72] proposed the Aesthetic Perspective Space (APS), a theoretical framework bringing together Intentionality (*ars musica* vs. *as informatica*) and Indexicality (sonic materiality, i.e., concrete vs. abstract) of both sonifications and electroacoustic music. Lindborg and collaborators [45] took a pragmatic approach to operationalize the APS in their study of sonifications of climate data, gathering textual, graphical, and sonic information to determine a range of project characteristics, which were reduced to five latent factors, or essential aspects: Action, Technical, Context, Perspective, and Visualization.

Sonification can communicate strongly. When presented with an artistic data sonification, listeners might find it exciting, which may then stimulate positive action. Buening et al. [78] focused on the capacity of data art to elicit an “artistic affectivization,” and demonstrated that it has a potential to lead to perspective-sharing within a community. In the context of data perceptualization (which includes sonification), an artwork is successful if it is able to simultaneously achieve both information transfer (e.g., an understanding of the science data) and affectivization (e.g., an emotional engagement with the subject matter in its context) [36].

### 3.1.3 Narrative

Two aspects of narrative need to be attended to. Firstly, experience, as in “narrative visualisations along a spectrum of author-driven and reader-driven approaches” [36]. Secondly, narrative tactics, which the authors understand as implying intentionality. Multi-modal approaches are complex but have a great potential for impact, not only for education and awareness, but also for involving people and stimulating action. Many projects in the DSA involve both sonification and visualization (note that DataViz, i.e., concurrent audio-visual data perceptualization, constitutes 29% of all projects), making them potentially very effective “tools for communicating a deeper understanding... to recast scientific knowledge into expressions that inform, engage, and excite... in a different way: via aesthetics and characteristics, artistic affectivization, narrative, and knowledge mapping” [36].

In their influential work, Segel and Heer [79] define narrative data visualization as “visualisation intended to convey stories.” In the design space of narrative visualizations, the role of the author and the user as drivers of the data experience sits along a continuum in which specific design decisions have to be taken in order to convey the intended message and engage the recipient with the phenomenon behind the dataset. Decisions taken in the design process depend on the purposes (the *Goals* of the DSA), the combination of visual supports used (in this case, the *MediaMix*), and the instructions provided to the final users. The latter angle was recently raised by [33] in an investigation of how authors’ self-reflection on their design choices might support people’s learning of how to listen to data. Nevertheless, according to Segel and Heer, these elements might eventually become less needed as the public gets used to narrative visualization, and, quite possibly, sonification as well.

Through the classification of the DSA projects, the authors see how “narrative sonification,” i.e., sonifications whose purpose is to engage the listener with the phenomenon behind the actual dataset rather than conveying analytical “numerical” values through sound, is an emerging though still largely implicit approach. Its analysis can lead to the definition of explicit criteria and narrative patterns [80] advancing sonification practice by providing a broader theoretical framework and design guidelines.

### 3.1.4 Intentionality

In this study, the authors presented how the number of sonifications created and shared with the goal of fostering a connection between the author, audience, and phenomenon behind the data has increased. In these projects, authors bend the definition of sonification itself (by, for instance, widening the choices of sound material to integrate speech) and broaden its scope to serve as a means of emotional engagement, if not explicitly of activism (such as in sonifications of climate change and the COVID pandemic). Along with established sonification methods, other practices seem to emerge that intend the audience to experience a phenomenon through sound without the mediation of (numerical) data. Inspired by autographic design approaches [81], autographic sonifications use sound “as a material—not an abstract—entity and a trace of real-world phenomena that we can read, decode, and understand without the mediation of representation” [82].

In the authors’ previous analysis of a subset of DSA projects [44], the analysis operationalized the APS (e.g., [83]) in which one dimension is defined as the degree of Indexicality of the sonic materials. This links to Emerson’s *Language Grid* concept [84]. In the context of music compositions, he defines “mimetic” as “the imitation not only of nature but also of aspects of human culture not usually associated directly with musical material” (p. 17). This perspective opens up new ways of listening to sonification. By attending to the sounds emitted by a specific phenomenon, listeners engage with and make sense of it (e.g., by decoding the intensity of a rainfall through the sound it produces or the behavior of a computer processor by the sound of its electrical circuits). In this case, the designer is rather a facilitator that collects and displays sound in a way that helps listeners in the sense-making process. Examples of autographic sonifications from the DSA include works such as “The Killing of Nadeem Nawara and Mohammed Abu Daher” [85] and “Wildfire” [86]. Again, awareness on how the field is evolving and the variety of intentions involved will support the definition of design processes that help authors make explicit the communicative dimensions of their productions and their agency [29] toward a wider adoption of sonification as a medium for data representation.

### 3.2 Limitations

The MIR method that was used in the present analysis was deliberately chosen to be quite general, extracting a conservatively small number of basic features. The results of the prediction modeling might have been stronger with a

more targeted feature selection. For example, several of the employed descriptors were timbral (i.e., derived from spectrograms) and might not have captured characteristics that would have been perceptually relevant for some of the sonifications, such as note onset density, rhythmic complexity, or speed. Future audio analysis and automatic classification could improve by covering such features.

The DSA is not even three years old. Like a toddler, it is precocious in some ways and pure potential in many other ways. It has grown very quickly since 2021, and this might have led to an over-emphasis on certain data fields to the detriment of others, which might have been ignored until recently. For example, looking at the *Micro-Topic* classification, the authors note that Astronomy, one of 24 subdivisions, takes up more than a quarter of the current projects. It might be beneficial to split it into two or more parts: for example, one dedicated to near-Earth astronomical data, another to distant stars and galaxies. One reason for this predominance might be that projects related to astronomical sonification were manually added by the curatorial team and by the broader astronomy community, stimulated by a recent publication that aimed at reviewing how sonification is used for the exploration, representation, and communication of astronomical phenomena [43].

More importantly, as pointed out by Groß-Vogt and colleagues: “While this [the DSA] is an interesting data set, it has an intrinsic bias due to being curated” [16]. As a crowd-sourced effort, the DSA cannot indeed be considered a comprehensive cataloguing effort. Nonetheless, and as explained above, the low barrier to enter (unlike academic conferences and scientific publications), coupled with the curatorial supervision, makes the DSA a (to date) unique place where the visitor can explore and appreciate the broader spectrum of sonification, from research to practice, from academia to the commercial world. In this sense, the present analysis will hopefully spark the conversation among sonification scholars and practitioners on the evolution of the field.

### 3.3 Future Work

The analysis performed in this study presents an opportunity to rethink the DSA’s classification process, re-considering the broader relationship between manual and automated curation. The heterogeneity among cases and the status of sonification as a discipline (defined pretheoretical above) and practice could have inclined the curators toward a top-down, manual approach. Moreover, at the inception of DSA, DSA, multimodal were not easily/publicly available, hindering the feasibility of automated analysis of such corpus. However, the results of the analysis encourage a reexamination of automating the classification of specific facets of a sonification project, like the *MediaMix*, leveraging on the specific features of emerging multimodal models such as the ones developed by OpenAI and Google.

As described above, the authors are currently exploring the potential of predictive models for automatic classification, especially for *MediaMix* and *Micro Topic*. They foresee that a bottom-up approach, involving authors’, de-

signers’, and artists’ direct participation in the classification and curation process becomes plausible, provided that the insights and knowledge codified through this study can be encapsulated in a format that, through the revision and creation of the categories used to catalogue new cases, will work as a guide that becomes integrated into the community-sourced process of extending the DSA further.

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## 5 APPENDIXES

- SupMat1-Metadata-Sonification-Archive.xlsx (<https://github.com/SonoSofisms/ears-eyes/blob/main/SupMat1-Metadata-Sonification-Archive.xlsx>)
- SupMat2-DSA354\_MIR30\_clusters.csv ([https://github.com/SonoSofisms/ears-eyes/blob/main/SupMat2-DSA354\\_MIR30\\_clusters.csv](https://github.com/SonoSofisms/ears-eyes/blob/main/SupMat2-DSA354_MIR30_clusters.csv))
- SupMat3-DSA445-text-MTL-DLDAex.xlsx (<https://github.com/SonoSofisms/ears-eyes/blob/main/SupMat3-DSA445-text-LDA.xlsx>)

## THE AUTHORS



PerMagnus Lindborg



Valentina Caiola



Manni Chen



Paolo Ciuccarelli



Sara Lenzi

PerMagnus Lindborg is a composer, sound artist, and researcher in sound perception and the first author of more than 150 compositions, media artworks, and scholarly publications. Working in higher education since 2005 (France, Singapore, Korea), PerMagnus received his Ph.D. from KTH Royal Institute of Technology, Stockholm, and is currently Associate Professor at the School of Creative Media at City University of Hong Kong, where he is Co-Director of SoundLab. He is Vice-President for Asia-Oceania of the International Computer Music Association.

Valentina Caiola is a Ph.D. student at the School of Creative Media, City University of Hong Kong. Her research focuses on multimodal data representation, particularly combining data visualization and sonification. She brings a communication and information design background from Politecnico di Milano and has experience as a UX Design researcher.

Manni Chen is a Ph.D. candidate in School of Creative Media, City University of Hong Kong. She worked as a sound engineer before, recording and mixing different types of sound and music. Currently, her research inter-

est is about AI applied in audio production, to explore the boundary line for this new sonic application.

Architect and Communication Designer, Paolo Ciuccarelli is Professor of Design and Founding Director of the Center for Design at Northeastern University, Boston, and founder of the DensityDesign Lab at Politecnico di Milano. His research focuses on the transformations that help make sense of complex phenomena through data and design.

Sound Designer and philosopher with a Ph.D. in design, Sara Lenzi is Research Fellow at the Ikerbasque Foundation for Science and at the Faculty of Engineering of the Universidad de Deusto in Bilbao, Spain. She is Visiting Researcher at the Critical Alarms Lab, Delft University of Technology; associate member of the Center for Design, Northeastern University; and member of the Advisory Board of the Design Research Society. Her research focuses on data sonification for AI-supported anomaly detection in complex networks and the development of design tools, processes, and methods for the design of efficient data to sound translations. She is co-founder and co-curator of the Data Sonification Archive.