Transforming Multimodal Data from Music Therapy Sessions into OMOP CDM Format

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Background:

Despite being employed as a therapeutic tool for more than 200 years, music therapy has only recently experienced significant growth; as of 2023, there are now more than 10’000 professional music therapists across 33 European countries, a number which has grown 10-fold in the last several decades **[1, 2]**. Efforts to record and analyze these therapeutic sessions quantitatively are likewise relatively recent. The nascent body of work that quantifies therapeutic music recordings has demonstrated considerable potential for assisting therapists in their therapeutic assessments, and by extension, assisting patients undergoing therapy **[3]**. Several factors, however, have hindered research progress on this topic: (1) it necessitates a heavily multidisciplinary approach, drawing from expertise in acoustic signal processing and data science, as well as (neuro)psychological topics and music theory, (2) patient cohorts are often very limited in size (< 100 participants) for a given mental profile and therapeutic approach, and (3) protocols for performance and data collection vary widely, which adds complexity to effective and efficient research collaborations between active research groups.

The work we present here represents a first step toward overcoming each of these challenges. We provide a template for extracting and transforming diverse data collected in the context of music therapy, we demonstrate that acoustic features can be used alongside other traditional observational health data within the OMOP common data model (CDM), and we enable standardized analyses of therapy-related data that will facilitate large-scale, federated research investigations without the need for sharing sensitive, patient-specific information between groups.

Methods:

As a proof of concept, we investigated data collected in prior work **[4]**. Briefly, the data was recorded during improvisational music therapy sessions, in which a therapist and patient improvised piano simultaneously, with the therapist following a consistent musical pattern **[5]**. Patients needed no prior musical experience. The cohort of this prior study included approximately 70 participants, with ages ranging from 23 - 62 and with a diagnosis of depression/depressive disorder, of which 43 completed up to 12 unique improvisational therapy sessions spaced 1 week apart (the other 27 participants exited the study prematurely at various stages). In addition to the musical data, the participants provided information about their prescription medications and prior diagnoses, and completed a battery of standardized psychological assessments at multiple timepoints. A total of 11 therapists conducted the sessions, and the performance and consistency of the therapists was manually reviewed and assigned an array of quality metrics.

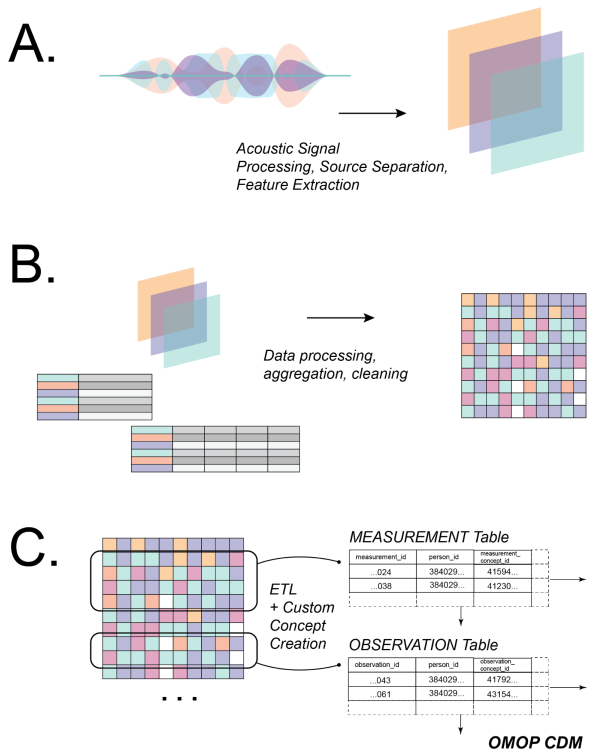

Figure 1. Three phases of transforming acoustic recordings into OMOP CDM format. (A) apply source separation techniques (for single mic ensemble recordings), apply filters, and extract relevant acoustic features. (B) Connect acoustic features with remaining preprocessed observational health data, coordinating links between patients and therapists. (C) Transform tabular data into OMOP CDM format, employing custom concepts where needed to capture acoustic-oriented measurements.

We transformed the various data in a three-stage process, outlined in **Figure 1**. We performed the extraction of acoustic features using a multi-agent improvisational beat tracking (MAIBT) algorithm developed and described in prior work **[6]**. The MAIBT algorithm determined the instantaneous tempo of the musical performance, and extracted metrical deviations (i.e. temporal differences between therapist and patient notes) for each of the recordings. The output of this algorithm made up the basis for the acoustic features we ultimately integrated into the OMOP dataset.

Once extracted, we combined the acoustic features with the patient-reported outcome measures and patient-reported experience measures (PROMS/PREMS), therapeutic diagnoses and procedural information, and therapist quality analyses in a single relational dataset. We cleaned and processed this data, ensuring consistency across patients and therapists, and then transformed the data into OMOP CDM format using the process described in **Figure 2** below:

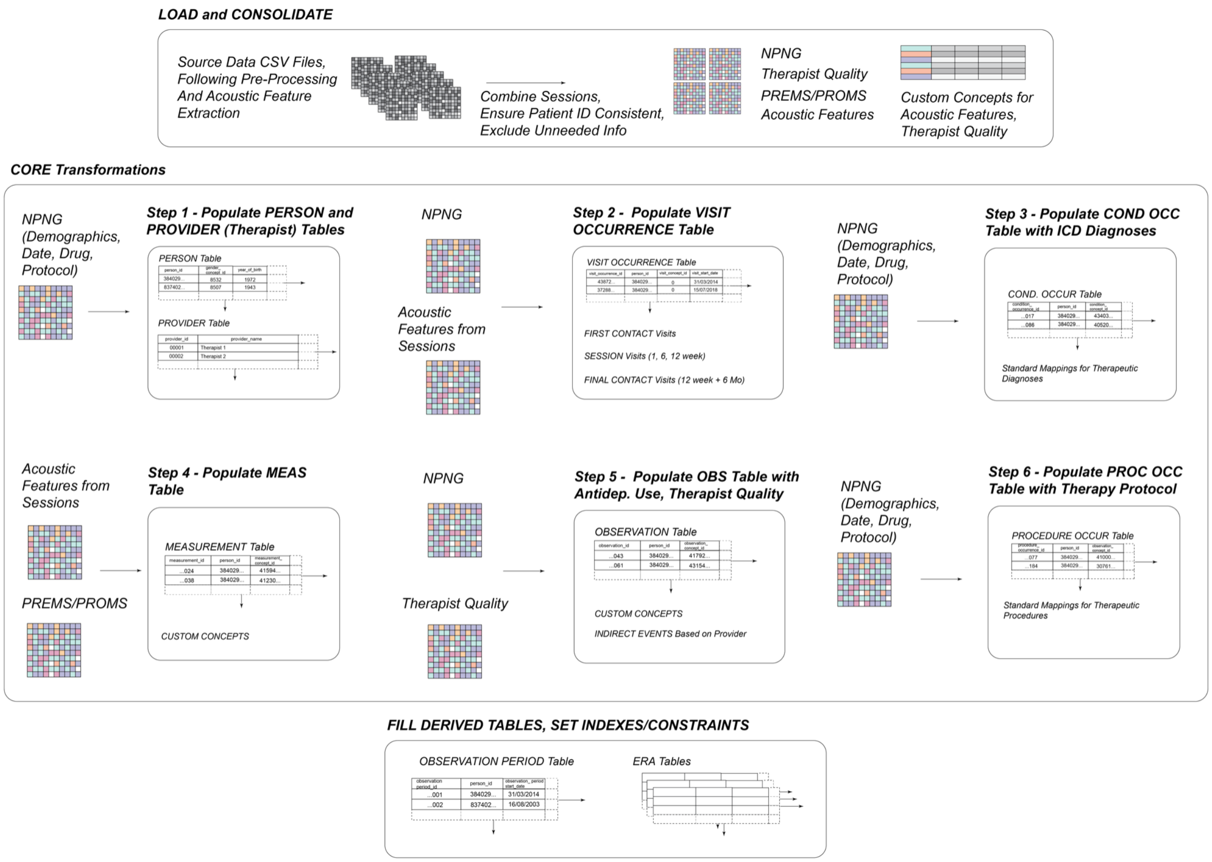

Figure 2. Transforming tabular music therapy data to OMOP CDM format proceeds in three phases, beginning with loading and consolidating the various tables into patient- and therapist-centric staging tables, then populating the various OMOP tables over 6 steps before completing the derived tables and preparing for integration into other OHDSI tooling.

We orchestrated the transformations using a single bash script containing psql utility commands that referenced an array of SQL statements. We packaged and deployed all scripts as a Docker container, after which we integrated the resulting OMOP CDM data with existing OHDSI tooling (Achilles & DQD for quality control, and Atlas/WebAPI for Cohort Creation and Model building).

Results:

Using the methods described above, we created a proof-of-concept (POC) dataset in OMOP CDM format for a limited number of patients (70 total, 43 continuous observation) based on data gathered during music therapy sessions. The resulting dataset contains approximately

60 events per continuously observed patient, most of which are measurements related to the musical improvisations. We have included an overview of the mapped concepts, domains and corresponding counts in **Table 1** below:

Table 1. Relevant OMOP concepts and counts in the POC OMOP dataset

Concept Description	OMOP Domain	Records[c]	Persons[c]
Standard Deviation Abs of Metrical Deviation [a]	Measurement	260	50
Standard Deviation of Metrical Deviation [a]	Measurement	260	50
Standard Deviation of Metrical Deviation Early [a]	Measurement	260	50
Standard Deviation of Metrical Deviation Late [a]	Measurement	260	50
Mean of Metrical Deviation [a]	Measurement	260	50
Mean of Metrical Deviation Early [a]	Measurement	260	50
Mean of Metrical Deviation Late [a]	Measurement	260	50
Mean Abs of Metrical Deviation [a]	Measurement	260	50
Number of notes after prune [a]	Measurement	260	50
Proportion of Notes Late [a]	Measurement	260	50
Montgomery-Åsberg depression rating scale	Measurement	90	40
Hospital anxiety and depression scale	Measurement	90	40
MOS SF-36: General health score	Measurement	90	40
Global assessment of functioning - 1993 DSMIV adaptation	Measurement	90	40
Music therapy	Procedure	70	70
Depressive disorder	Condition	60	60
Long-term current use of antidepressant medication	Observation	40	40
No evidence of	Observation	40	40
Listening skill exercises	Procedure	40	40
Breathing exercise education	Procedure	40	40
Recurrent depression	Condition	20	20
Therapist plays bourdon consistently [a, b, d]	Observation	20	20
Therapist and patient harmonizing and T infl. P [a, b, d]	Observation	20	20
Therapist and patient harmonizing [a, b, d]	Observation	10	10
Therapist and patient harmonizing, T infl. P and P infl. T [a, b, d]	Observation	10	10

[a] Custom concept defined to capture source-specific information
[b] Translation from Dutch description
[c] Counts rounded to nearest 10
[d] Concepts scored manually based on recording and related to both therapist (here, Provider) and patient

With this data, we have thus far validated prior work describing trends in musical synchronicity between therapists and patients, and the therapeutic outcomes of those patients **[4]**. One major limitation of this POC dataset, as discussed above, is its size; such a limitation hampers our ability to create generalizable models and extract robust insights. The approach, however, represents a first step toward producing larger, standardized datasets collected across diverse patient cohorts during music therapy sessions. We expect to build on this work and establish a federated network of music therapists, both within Europe and beyond, in the coming months. An important motivation for implementing musical features into observational health data in such a network is that unlike verbal interactions, interpersonal musical (and more generally, nonverbal) interactions are largely consistent across national and cultural boundaries **[7]**. For this reason, we expect that a multicultural and diverse federated network of music therapists would have potential to produce new and exciting insights into the general effects of nonverbal communication and phatic behavior on therapeutic outcomes.

Conclusions:

To our knowledge, this work represents the first attempt to harmonize acoustic information recorded during music therapy sessions into the OMOP CDM. Such a transformation has potential to improve mechanistic understandings in the music therapy field; the approach may also be extended to other areas of medicine where acoustic measurements may have clinical significance, such as linking neurological disorders with speech recordings, or linking heart valve defects with recordings from electronic stethoscopes.

References:

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