Synthetic Data in Communication Sciences and Disorders: A Methodological Investigation of Factors Affecting Utility in Simulated Datasets

James C. Borders1, Austin Thompson2, & Elaine Kearney3,4

1. Department of Biobehavioral Sciences, Teachers College Columbia University
2. Department of Communication Sciences and Disorders, University of Houston
3. School of Health and Rehabilitation Sciences, University of Queensland, Brisbane, Australia
4. Department of Speech Pathology, Princess Alexandra Hospital, Brisbane, Australia

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**Corresponding Author**:  
James C. Borders, PhD, CCC-SLP  
jcb2271@tc.columbia.edu

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# Abstract

**Purpose**: Reproducibility is a core principle of science and access to a study’s data is essential to reproduce its findings. However, data sharing is uncommon in the field of Communication Sciences and Disorders (CSD), often due to concerns related to privacy and disclosure risks. Synthetic data offers a potential solution to this barrier by generating artificial datasets that do not represent real individuals yet retain statistical properties and relationships from the original data. This study aimed to systematically evaluate the utility of synthetic data generation to promote transparency and reproducibility in the field of CSD and to identify factors that may influence its accuracy in maintaining statistical relationships.

**Method**: Three hypothetical study designs were simulated using the *simstudy* R package (Goldfeld & Wujciak-Jens, 2020). Within each design, various dataset parameters (sample size, hierarchical data structure, and between- and within-subject variability) were simulated to compare the utility of synthetic data with the original data. Synthetic data was generated with the *synthpop* R package (Nowok et al., 2016). The standardized ratio of the propensity mean squared error (*S\_pMSE*) was calculated to assess whether relationships between variables were maintained in the synthetic dataset compared to the original data.

**Results**: Synthetic datasets maintained the direction of *p*-values in six out of the nine studies and effect size categorizations in five studies. In cases where synthetic datasets did not maintain 95% of the inferential or effect size results, the absolute mean difference between synthetic and original datasets was relatively low, suggesting that the distribution of results from synthetic datasets closely approximated the alpha or effect size categorization threshold.

**Conclusion**: Findings suggest that synthetic data can be applied to research in the field of CSD, maintaining statistical properties and relationships in some datasets. However, factors such as hierarchical data structures and small sample sizes may impact the precision of synthetic data. Researchers using synthetic data should assess its stability in preserving their results. Overall, synthetic data provides a feasible approach to transparently demonstrate data analysis steps, including data pre-processing and statistical modeling.

# Introduction

Transparency and openness are fundamental tenets of science, with computational reproducibility playing a key role in maintaining these values. Computational reproducibility refers to the ability to recreate a study’s results using the original data. Nowadays, the vast majority of scientific studies use some degree of computation in processing data, conducting descriptive or inferential statistics, and visualizing results. When these computations are reproducible, the transparency and confidence in findings are enhanced. Achieving computational reproducibility, however, requires authors to share their data. Both the National Institutes of Health and the National Science Foundation mandate data sharing and management plans to ensure that scientific data supporting a study is shared upon publication and aligns with FAIR (Findability, Accessibility, Interoperability, and Reuse) principles of digital assets (Watson et al., 2023; Wilkinson et al., 2016).

Providing open, publicly available data benefits scientists, funding bodies, and society at large by enabling researchers to verify results, generate new knowledge (e.g., meta-analyses, secondary analyses), develop hypotheses, and minimize redundant data collection (Chow et al., 2023). In this sense, sharing data promotes a cumulative and self-correcting science. Despite the clear benefits of open data and its growing adoption in other fields like psychology and the biobehavioral sciences (Quintana, 2020), only 26% of a sample of researchers in the field of Communication Sciences and Disorders (CSD) reported sharing their data publicly at least once (El Amin et al., 2023).

Understanding the nuances of data sharing requires a closer look at the different types of data generated throughout a research project’s life cycle. These include raw collected data, processed intermediate data, and final analysis data (Table 1). However, a common misconception is that open data refers solely to sharing raw data (e.g., audio recordings, videos, MRI data) (Pfeiffer et al., 2024). In reality, sharing intermediate or analysis data can also support reproducibility while reducing privacy and confidentiality concerns associated with sharing raw data. However, these different types of data offer varying levels of utility: sharing raw data enables maximum reproducibility and secondary research opportunities, while analysis data (although easier to share) primarily supports computational reproducibility.

##### Table 1 here.

Both individual and system-level barriers hinder data sharing, including a lack of time, knowledge, support from colleagues, and perceived incentives (Pfeiffer et al., 2024). Furthermore, each type of data comes with unique challenges regarding data sharing. For raw data, it is common that researchers often do not obtain consent to share data or cannot contact participants after data collection. Additionally, sharing de-identified raw or intermediate data may require additional approval from the institutional review board. Even when de-identification is possible, anonymized intermediate or analysis datasets can still carry re-identification risks, especially in small samples or vulnerable populations where indirect identifiers (e.g., gender, age, or race) may compromise participant confidentiality (Rocher et al., 2019). Therefore, although sharing de-identified analysis data is the minimum requirement for ensuring computational reproducibility and promoting cumulative science, concerns about privacy must be addressed when sharing sensitive data.

***Synthetic Data as an Approach to Promote Transparency and Reproducibility***

Synthetic data generation offers a promising solution to safeguarding participants’ privacy and confidentiality in publicly available datasets (Drechsler & Haensch, 2024; Rubin, 1993). This approach involves creating artificial datasets that do not represent real individuals, thereby significantly reducing the risk of disclosure. Importantly, synthetic data retains the statistical properties and relationships of the original data, enabling readers to evaluate key aspects of the study’s analysis workflow (e.g., data pre-processing, statistical modeling), reproduce findings, explore datasets, and develop new questions or hypotheses. Synthetic data generation is widely used across medical research, industry, and government agencies, most notably by the United States Census Bureau (Jarmin et al., 2014). Although the concept of synthetic data methods was first introduced more than 30 years ago (Rubin, 1993), recent analytic and software developments have streamlined the process, making it easier and more efficient to generate high-quality synthetic data (Nowok et al., 2016).

The intended use of synthetic data influences the level of rigor and scrutiny required. For example, synthetic data can serve as a pedagogical tool to teach data analysis skills or novel statistical methods (Shepherd et al. 2017). In such cases, preserving general statistical properties is sufficient, even if precise relationships between variables are not fully maintained. Similarly, synthetic data accompanying publications can facilitate reproducible workflows to illustrate data pre-processing steps or statistical models without replicating exact study results. However, when synthetic data is used for hypothesis testing, meta-analyses, or methodological development, higher standards are required (Raab et al., 2017). In these scenarios, synthetic datasets must accurately preserve multivariable relationships to ensure their validity and utility.

Two main approaches are used to assess the utility of synthetic datasets: general and specific utility (Snoke et al., 2018). General utility evaluates whether the synthetic dataset maintains the overall statistical properties and multivariable relationships of the original dataset. This includes visual comparisons of univariate distributions (e.g.., bar charts, histograms) and bivariate joint distributions (e.g., scatterplots), as well as direct comparisons to examine the predicted probability that a record comes from the synthetic data (e.g., propensity mean squared error; *pMSE*). Specific utility assesses whether inferential relationships from the original dataset are preserved in the synthetic dataset by comparing model fit indices and coefficients.

***Application of Synthetic Data in Communication Sciences and Disorders***

Despite the potential utility of synthetic data to promote data sharing in the field of CSD, this approach is not widely known or adopted. Data commonly collected in CSD research poses unique challenges, including smaller sample sizes than are typically recommended for synthetic data generation and a wide range of study designs, outcomes, and analyses (Borders et al., 2022; Gaeta & Brydges, 2020). Furthermore, reproducible workflows that outline important steps to wrangle or model datasets are rarely provided in publications, hindering the transparency and reproducibility of scientific literature.

Therefore, the present study aimed to evaluate the utility of synthetic data in different datasets that resemble CSD. Since there is a paucity of publicly available data in the field that may also introduce selection bias, this study used a data simulation approach to systematically examine differences in synthetic data generation across different data parameters. This involved simulating datasets under different designs and with different characteristics (e.g., sample size, variability, hierarchical or aggregated structure). We hypothesized that synthetic datasets would maintain the statistical properties (general utility) and inferential results (specific utility) of the original datasets, and that synthetic data would remain stable when generating multiple datasets. A separate tutorial outlining steps to implement and evaluate synthetic data is available for interested readers (**tutorial citation here**).

# Method

## Data Simulation

*Scenario A*

XXX

*Scenario B*

XXX

*Scenario C*

XXX

Authors performed a manual search to identify publicly available datasets from previously published research articles related to the ‘Big Nine’ ASHA domains: swallowing (Curtis et al., 2023), articulation (Thompson et al., 2023), fluency (Elsherif et al., 2021), voice and resonance (Novotný et al., 2016), hearing (Battal et al., 2019), communication modalities (King et al., 2022), receptive and expressive language (Kearney et al., 2023; Ayin et al., 2024), cognitive aspects of communication (Clough et al., 2023), and social aspects of communication (Chanchaochai & Schwarz, 2023). These studies were classified by their research design, population, and statistical analysis (Table 2).

It is important to note that not all research designs are represented due to the limited availability of public data in the field of CSD and the inherent challenge of including all possible designs. Instead, this approach prioritizes representation across all CSD subfields to provide a proof of concept for the reader. To demonstrate the feasibility and potential utility of synthetic data to promote transparency and reproducibility, an analysis was chosen from each study to generate synthetic data for those variables.

##### Table 2 here.

## Generation of Synthetic Datasets with the Synthpop Package

Synthetic data generation and statistical analyses were conducted in R version 4.2.1 (R Core Team, 2022). The *synthpop* package (version 1.8.0) (Nowok et al., 2016) was used to generate synthetic data via complete conditional specification (Drechsler 2011). This method synthesizes data one variable at a time: the first variable is generated by random sampling from the original dataset, and subsequent variables are synthesized conditionally based on previously synthesized variables. This stepwise approach captures relationships between variables incrementally rather than attempting to synthesize all relationships simultaneously.

For example, consider a dataset containing three variables: participant ID, vowel space area, and intelligibility. The process would begin by synthesizing participant ID through random sampling from its observed distribution. Vowel space area would then be synthesized conditionally based on the synthetic participant ID values, with synthetic values drawn from predictions informed by the original data. Finally, intelligibility would be synthesized conditionally on both participant ID and vowel space area, with synthetic values similarly sampled from predictions.

*Synthpop* inherently manages missing data and maintains relationships between missingness and other variables using a tree-based algorithm, specifically classification and regression trees (CART), for data synthesis (Nowok et al., 2016). Alternatively, users can select other tree-based methods, such as random forests, or parametric models like linear or logistic regression. This process resembles multiple imputation by chained equations (MICE) for handling missing data (van Buuren, 2018) but with a key distinction: instead of imputing only missing values, synthpop generates entirely synthetic data (Raghunathan, 2021), significantly reducing disclosure risk.

Nowok et al. (2016) provide an in-depth overview of the *synthpop* package’s features. Briefly, synthesis is largely automated using the syn() function. Users can customize various options, including the modeling approach, the synthesis order of variables, the choice of predictors, smoothing parameters for continuous variables to enhance privacy, and rules for maintaining logical relationships. A detailed tutorial is available for further guidance on code implementation and utility evaluation (Tutorial Citation Here).

***Evaluation of Utility for Synthetic Datasets***

In the present study, we aimed to illustrate the feasibility of synthetic data to promote transparency and reproducibility for CSD datasets, as well as determine the utility of synthetic data across a range of datasets in CSD. Utility was defined as either specific or general.

To evaluate specific utility, we selected a statistical analysis from the original study and generated 100 different synthetic datasets for each original dataset from an ASHA ‘Big Nine’ domain. A statistical model with the original dataset was fit, and the *p*-value and effect size were recorded. If 95% of *p*-values and effect sizes from the synthetic datasets demonstrated a similar result as the original study, then this indicated that synthetic data maintained the statistical relationship. Specifically, we further defined this as a similar inferential result for *p*-values (i.e., a ‘significant’ or ‘non-significant’ *p*-value based on the original study’s alpha level) and effect sizes that maintained their categorization based on conventional thresholds (e.g., a ‘medium’ effect size). Measures of effect size and their interpretation for each study are provided in Table 3. If variability between the 100 synthetic datasets was appreciated, we visualized and described the dispersion of this distribution.

Since Curtis et al. (2023) did not perform inferential tests, we directly compared each synthetic dataset to the original data with a zero-inflated beta multilevel model with the *gamlss* package (version 5.4.3) (Stasinopoulos & Rigby, 2007). This model included fixed effects of dataset type (synthetic/original) and bolus consistency (thin liquid/extremely thick/regular), and a random intercept of participant. Due to issues with model convergence, the fixed effect structure was simplified to only include dataset type. The *p*-value from both zero-inflated and beta portions of the model were evaluated and *p* < .05 was interpreted no statistically significant difference between the synthetic and original dataset.

To evaluate general utility, we examined visual comparisons of univariate distributions (e.g.., bar charts, histograms) and bivariate joint distributions (e.g., scatterplots) from the first synthetic dataset generated. The analysis plan for this study was preregistered on the Open Science Framework (<https://osf.io/vhgq2>).

##### Table 3 here.

# Results

*Swallowing*

Curtis et al. (2023) examined normative reference values for swallowing outcomes during flexible endoscopic evaluations of swallowing among 39 non-dysphagic, community-dwelling adults. In this observational cohort study, participants were administered 15 swallowing trials that varied by bolus size, consistency, contrast agent, and swallowing instructions. A variety of swallowing outcomes were measured, including the amount of laryngeal vestibule residue. Median and interquartile ranges (IQR) were used to describe the distribution of laryngeal vestibule residue ratings.

Figure 1 here.

Descriptively, the synthetic dataset classified 64% of laryngeal vestibule ratings on thin liquid boluses as ‘absent’ (i.e., 0% residue) compared to 68% in the original dataset. In the synthetic dataset, the median value on thin liquids was 0.03 (IQR: 0.02 - 0.045) compared to 0.03 (IQR: 0.02 - 0.04) in the original dataset. 98.61% of extremely thick liquids were classified as having no laryngeal vestibule residue compared to 100% in the original dataset. A similar pattern was appreciated for regular solids (96.43% in synthetic vs. 100% in original dataset). When examined across 100 synthetic datasets, findings from the zero-inflated beta multilevel models indicate that 100% and 98% of synthetic datasets were not statistically significantly different than the original dataset for the zero-inflated and beta portions of the model, respectively (Table 4). Additionally, effect size categorizations were maintained for 100% of both zero-inflated and beta portions of the model.

*Articulation*

Thompson et al. (2023) examined the relationship between vowel space area and speech intelligibility among 40 speakers with dysarthria of varying etiologies, including Parkinson’s disease, amyotrophic lateral sclerosis, Huntington’s disease, and cerebellar ataxia. A linear regression model revealed a statistically significant relationship between vowel space area and intelligibility (*p* < .001) with a Cohen’s *f* of 0.59, corresponding to a conventionally “large” effect size (Table 3).

Figure 2 here.

Findings from the 100 generated synthetic datasets indicate that 71% of datasets demonstrated the same inferential result (i.e., a statistically significant *p*-value). For the effect size, 57% of synthetic datasets maintained a ‘large’ effect size categorization.

*Fluency* (Elsherif et al., 2021)

*Voice and resonance* (Novotný et al., 2016)

*Hearing* (Battal et al., 2019)

*Communication modalities* (King et al., 2022)

*Receptive and expressive language* (Kearney et al., 2023; Ayin et al., 2024)

*Cognitive aspects of communication* (Clough et al., 2023),

*Social aspects of communication* (Chanchaochai & Schwarz, 2023)

### Results for Studies 3 - 9

Studies in the domains of fluency, voice and resonance, communication modalities, receptive and expressive language, and social aspects of communication demonstrated more than 95% *p*-value agreement between the original and synthetic datasets (Table 3). Among studies that demonstrated lower agreement, the absolute mean difference between the synthetic *p*-values and the original *p*-value was 0.05 (*SD* = 0.1) for articulation, 0.03 (*SD* = 0.04) for hearing, and 0.25 (*SD* = 0.28) for cognitive aspects of communication (Figure 3). For effect size categorization agreement, studies in the domains of fluency, hearing, communication modalities, and cognitive aspects of communication maintained the effect size categorization of the original study. Among studies that demonstrated lower effect size cateogrization agreement, the absolute mean difference between the effect size from synthetic datasets and the original study’s effect size was 0.19 (SD = 0.12) for articulation, 0.09 (*SD* = 0.07) for voice and resonance, 0.06 (*SD* = 0.05) for receptive and expressive language, and 0.21 (*SD* = 0.2) for social aspects of communication.

##### Figure 3 here.

##### Figure 4 here.

##### Table 4 here.

# Discussion

Although computational reproducibility is a core principle of science, data sharing is uncommon in CSD, partly due to concerns regarding disclosure risk (Pfeiffer et al., 2024). This study demonstrates the utility of synthetic datasets to protect participant confidentiality while preserving the statistical properties and relationships of the original analysis data. The utility of synthetic data is further strengthened by the range of datasets included in the current study, which varied by domain (across nine ASHA domains), sample size (from 40 to >8,000 data points), statistical models (from simple correlations to multilevel model with 3-way interactions), and effect sizes (from conventionally “small” to “large”). These results suggest that synthetic datasets can be effectively used across a wide range of studies in the field of CSD to preserve participant confidentiality when sharing data.

One key finding is that lower agreement between synthetic and original datasets was not attributed to sample size, despite the *synthpop* package’s recommendation of a minimum of 130 observations for generating synthetic datasets (Nowok et al., 2016). For example, in the original study from the cognition domain, which included over 8,000 observations, only 35% of synthetic datasets maintained the same inferential result as the original dataset. Instead, *p*-value and effect size agreement between the synthetic and original datasets was influenced by the original data’s proximity to the statistical significance or effect size thresholds. For example, the original cognition study reported a *p*-value of .013, resulting in a 35% agreement rate for synthetic datasets. Conversely, studies that reported an original *p*-value of <.001 showed a *p*-value agreement rate of 97-100%, with the exception of the articulation study, which had a *p*-value agreement of 71%.

These findings highlight the importance of verifying the accuracy of synthetic datasets and providing these comparisons in supplemental manuscript materials. To ensure synthetic data quality, researchers should generate multiple versions of a synthetic dataset and select the one that most closely reproduces the statistical findings of the original analysis. If the synthetic dataset fails to sufficiently maintain these relationships, it should not be shared.

This study is not without limitations. First, studies were selected in the present study because they were openly available and represented different subfields within CSD. Therefore, selection bias is likely present, and these studies are not representative of every research design or data parameter that a researcher may encounter. However, it is imperative that the user evaluate the utility of synthetic data in the context of their goals (e.g., educational, workflow transparency, or meta-analysis/hypothesis generation) before publicly sharing the dataset. Additionally, we used predetermined thresholds (e.g., ‘significant’ *p*-values and effect size categories) to evaluate whether synthetic data maintained the relationships observed in the original study. When the original analyses had *p*-values near the threshold for significance (e.g., .01 < *p* < .05) or effect sizes near the boundary of a category, lower agreement was more likely. This likely reflects the distribution of synthetic data across both sides of these thresholds rather than actual poor agreement (Figures 3 & 4). Additionally, it’s important to recognize that synthetic data is inherently a proxy and cannot entirely preserve all statistical properties of the original dataset. Therefore, researchers should provide de-identified (or identifiable when ethical approval is obtained) data whenever possible, as well as evaluate the utility of the synthetic dataset in the context of their own study. Finally, open data alone does not ensure computational reproducibility. Instead, both open data and accompanied code or syntax is required to reproduce analyses. In fact, recent research showed that a high percentage of findings from registered reports that provided open data were unable to be reproduced (Obels et al., 2020). Reproducible workflows in languages like R have been proposed and warrant consideration (Peikert et al., 2021).

## Data Sharing Framework

In this framework, we aim to empower researchers who may feel uncertain or unmotivated to consider data sharing for their current or future work. We begin by examining the scientific and ethical implications of closed data, followed by an evaluation of the commonly used “available upon request” approach to data sharing, which we argue is insufficient. Finally, we outline the benefits of open data practices, emphasizing that sharing different types of data (raw, intermediate, analysis, and synthetic) can offer various levels of utility and impact.

### Ethical and Scientific Need for Open Data

Closed data impedes cumulative science and raises ethical concerns. Researchers have an ethical responsibility to maximize the use of clinical data, as participants typically enroll in research with the expectation that their data will help answer important public health questions. In fact, studies on participants’ motivations, particularly in non-experimental, observational research where there is no direct benefit, show that altruism is a key factor for participation (i.e., “I signed up because this study might be able to help future patients in my situation”) (Soule MD et al., 2016). Thus, it is essential that researchers ensure participants’ data is fully utilized to benefit future patients, clinical outcomes, and scientific knowledge.

Additionally, many research questions cannot be fully answered in a single study due to limitations like small or unrepresentative samples. Sharing data extends the value of collected datasets and allows other researchers to build on previous findings. Closed data practices also place an undue burden on future participants, particularly in studies involving invasive methodologies (e.g., radiation from videofluoroscopic swallow studies or neuroimaging) or require extensive travel and time. If previously collected data is not shared, future participants may undergo unnecessary procedures to duplicate these data.

Researchers conducting publicly funded studies are also ethically obligated to return data to the public that financed their research, a responsibility increasingly emphasized by funding agencies such as the National Institutes of Health and the National Science Foundation (Watson et al., 2023; Wilkinson et al., 2016). Even in cases where research is privately funded, participants arguably have the right to see their data shared and used to its fullest potential. In our experience, when participants are informed during the consent process about the potential for their data to be shared and reused, they overwhelmingly support data sharing to maximize the impact of their contribution.

Although some researchers may consider data availability statements like “available upon reasonable request” as a step toward data sharing, recent research has shown poor compliance with less than half of studies providing requested data (Tedersoo et al., 2021). In many cases, researchers do not devote the time to properly organize their data, thereby hindering its availability when requested or may restrict access to protect their data from reuse. Moreover, purposefully vague and unclear data availability statements may exacerbate inequities in the field. This practice limits access, particularly for those with fewer resources or opportunities, and poses a direct barrier to a cumulative and transparent scientific literature.

### Benefits of Open Data

Open data offers substantial benefits for both the scientific community and researcher. For example, studies show that openly shared data is associated with higher citation rates for the original work (Drachen et al., 2016; Piwowar et al., 2007; Piwowar & Vision, 2013). However, sharing data is not always straightforward, and researchers must consider when and what types of data to share. Figure 5 proposes a decision tree to guide researchers through the process of deciding which type of data to share. For practical guides on obtaining consent, sharing data, and ensuring FAIR data principles, we direct our readers to (Ohmann et al., 2017). Different types of data can be shared, including raw, intermediate, analysis, and synthetic data (Table 1), each providing varying levels of utility and benefit.

##### Figure 5 here.

**Analysis Data.** Sharing analysis data enables others to verify results during peer review or post-publication, promoting a more transparent and reliable scientific record. This practice also allows science to be self-correcting (Vazire & Holcombe, 2022). Analysis data is particularly important for meta-analyses, as these depend on comprehensive reporting of descriptive statistics. Unfortunately, many studies do not report all necessary details (e.g., means, standard deviations, and sample sizes) or use different statistical analyses, making it challenging to synthesize results across studies. Sharing analysis datasets can fill this gap, allowing more studies to be included in meta-analyses and resulting in more robust analyses (e.g., individual participant meta-analysis) (Eisenhauer, 2021; Yu & Romero, 2024) and conclusions (Chow et al., 2023), which is especially valuable for studying low-incidence populations in fields like CSD.

**Raw or Intermediate Data.** Sharing raw or intermediate data further enhances transparency by enabling researchers to reproduce the calculations behind analysis data. Different operational definitions or analysis steps are often a barrier to inclusion in a meta-analysis. Sharing this type of data ensures that secondary analyses can be performed with alternate methodologies or operational definitions, as the field progresses. In this sense, sharing raw or intermediate data facilitates the generation of new knowledge and accelerates scientific discovery. Despite its many benefits, there are instances where sharing raw or intermediate data may not be feasible. For example, researchers may not have obtained consent from participants for data sharing, or the institutional review board may impose project-specific guidelines that restrict sharing this type of data. Even de-identified data may carry risks, as participants could be re-identified through indirect identifiers.

**Synthetic Data.** In such cases, synthetic data offers a viable alternative. Synthetic data maintains the statistical properties of the original data while protecting participant privacy, thus facilitating computational reproducibility. In this study, we demonstrated how synthetic data can be generated using the *synthpop* package in R across a wide range of datasets in the field of CSD. Recognizing that coding expertise may be a barrier for some researchers, we have also developed a free Shiny website that interfaces with *synthpop*, allowing researchers to easily generate synthetic versions of their data (https://csdsynthetic.shinyapps.io/synthetic\_data\_generation/).

## Moving Forward

Current training models and incentive structures are not well-equipped to promote data sharing. To encourage open science practices like data sharing, larger systemic changes are likely necessary at both the organizational level (e.g., ASHA, societies) and within academic institutions. For example, doctoral programs should offer coursework that introduces these concepts and educates future researchers on best practices for data sharing. Fortunately, many resources are available for current researchers to familiarize themselves with these practices (Lewis, 2024). Additionally, institutions must incentivize data sharing and recognize open science efforts as valuable scholarly contributions. Although ASHA has introduced open science badges to acknowledge these efforts, it remains unclear if this is enough to encourage large-scale participation. Ultimately, a broader cultural shift is needed in the field - from the current individualistic, siloed approach to a more collaborative and pro-social view of science.

## Conclusions

This study assessed the utility of the *synthpop* package in R for generating synthetic data in situations where sharing original data poses risks of participant re-identification. We demonstrated that synthetic data can be effectively applied across various data types and research areas within the CSD field. In most cases, the synthetic data closely matched the *p*-values and effect sizes of the original data, though a few instances showed lower agreement. Therefore, researchers using synthetic data should verify its accuracy in reproducing their original findings before sharing. Finally, we provide a framework for data sharing, emphasizing that whether researchers share raw, intermediate, analysis, or synthetic data, some form of data sharing is achievable for all. Our overarching goal is to establish data sharing as the standard practice, rather than the exception, in CSD.

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# Table and Figure Captions

Table 1: Description of types of data.

Table 2: Characteristics of included studies by ASHA domain.

Table 3: Effect size measures and interpretation by statistical test.

Table 4: Stability of synthetic datasets across ASHA domains.

Figure 1. Visualization of data distributions from synthetic and original data for Study #1 (Curtis et al., 2023).

*Caption*: Panel A displays the overall distribution of laryngeal vestibule residue. Panel B displays the frequency of values by bolus consistency.

Figure 2. Visualization of data distributions from synthetic and original data for Study #2 (Thompson et al., 2023).

*Caption*: Panel A displays the distribution of vowel space area and panel B displays the distribution of speech intelligibility.

Figure 3. Distribution of log-transformed *p*-values in synthetic datasets across ASHA domains.

*Caption*: Each panel displays the distribution of log-transformed *p*-values across 100 synthetic datasets for a given ASHA domain. The dashed line indicates the threshold for statistical significance from the original study. Shaded green areas indicate synthetic *p*-values that maintained the statistical inferential result of the original study. The mean difference and standard deviation of raw *p*-values compared to the *p*-value reported in the original study is shown below each panel’s title.

Figure 4. Distribution of effect sizes in synthetic datasets across ASHA domains.

*Caption*: Each panel displays the distribution of effect sizes across 100 synthetic datasets for a given ASHA domain. The dashed line indicates the effect size reported in the original study and the light blue shaded area indicates the range of the effect size categorization. The mean difference and standard deviation of the effect size compared to the result reported in the original study is shown below each panel’s title.

Figure 5. Decision tree for data sharing.