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META-ANALYSIS METHOD TO EVALUATE EMG COMPRESSION TECHNIQUES: A SYSTEMATIC REVIEW

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ABSTRACT

Modern technology allows for the development of improved telehealth monitor and care systems for patients who are in rural areas. Due to very effective biological signal data compression and reconstruction technologies, it is now conceivable. Several researchers have created and used a variety of EMG compression and reconstruction techniques over the last 20 years. The process of data compression involves lowering the number of bits required to present the data. It is done to reduce bandwidth of the network, free up storage space, and fast transfer of data while preserving passable signal quality. Performance indicators including the percentage root mean square difference (PRD) and Compression Factor (CF) were examined and compared for these approaches. High CF increases savings but lowers the signal quality that is compressed. Increased PRD increases the quality at the cost of CF. Hence, CF and PRD need to be in balanced.

The review and analysis of 21 PRD and CF-based published papers is the main emphasis of this study. CF and signal reconstruction quality, which is assessed through PRD, are of utmost importance for an effective compression. The correlation among these two is taken into consideration because they are both dependent characteristics. Because it is a systematic and statistical procedure that combines the findings of earlier studies, offers a common answer, and identifies similarities and comparative behavior among many studies, meta-analysis is utilized for analysis.

The aggregate correlation value of all 21 (To maintain data homogeneity, three studies were excluded) research works, is 0.77, and this number is used to categorize the works. Due of the analysis's 13.86% heterogeneity (I^2) result, all research papers fall under the same category.

In [16], researchers utilized a sample size of 80 and employed a two-dimensional approach for compression, specifically using a recurrent pattern matching algorithm called the multi-dimensional multiscale parser (MMP). According to the statistical analysis in the study, de Melo WC (2016) achieved an average PRD of 6.40, indicating a close resemblance between the original and reconstructed EMG signals. Additionally, the study reported a higher CF of

82.50, indicating a significant reduction in data size. This work offers methods for validating upcoming EMG compression and reconstruction techniques based on the link between CR and PRD.

Keywords: EMG Compression; Meta-Analysis; Compression Factor (CF); Percentage Root Mean Square Difference (PRD)

1. Introduction

The medical care system has evolved in the current technological era to help patients even when they don't need to physically visit a doctor. It is now possible to establish wired and wireless communication linkages between a patient and a medical specialist via phone, email, video conferencing, etc. thanks to technological advancements. ECG, EMG, and other medical data sets are captured form patients' medical records using specific recorders, and when the data has been processed appropriately, it is sent to medical professionals for review. To assess a patient's health and the functionality of their muscles, EMG signals are recorded. If ECG or EMG signals are repeatedly captured for use in a patient monitoring and care system, a huge amount of data will result. Because of this, the objective of EMG signal compression is to reduce the quantity of EMG data that must be transferred or retained while maintaining clinically acceptable signal quality and a manageable level of implementation complexity. For both isometric and isotonic exercise, methods for compressing EMG signals have been thoroughly studied during the past few decades.

There are two types of compression techniques: lossy and loss less. For lossless compression techniques, the compression factor is relatively small. While lossy compression methods do not replicate the original signals, they do have a higher compression factor. Therefore, the quality of the replicated signal and compression factor are always in trade-off.

Several methods are documented in the literature that are based on linear and non-linear transform like Discrete Wavelet Transforms (DWT) and Discrete Cosine Transforms (DCT) [4, 5, 10, 15, 18, 21, 23], modified DWT [13, 15, 17], swarm based [1], DPCM [3, 4], Vector quantization [2], artificial neural network [23] and image encoders JPEG2000 and video encoder H.264/AVC [6, 7, 8, 11, 12, 14, 16, 19, 20]. Furthermore, researchers are striving to show the trade-off between computational complexity and distortions in reconstructed signals [22].

JPEG2000 encoder (used to compress the image signal) and H.264/AVC (video encoder) were tested by Costa et al. [7, 8, 11, and 12] to demonstrate that they may also be used to compress EMG signals and achieved a higher compression factor when compared to alternatives. For the required outcomes, they additionally applied DWT with entropy encoding [5] and spectrum segmentation [18]. The Artificial Bee Colony (ABC) swarm algorithm is used by Hosney et al. [1] in 2018 to choose the ideal characteristics of bio signals like ECG, EMG and EEG, needed to preserve the reconstructed signal's quality for certain compression factor. To extract those features, they make use of Tchebichef moments. When comparing the compression of EMG signals using DCT and DWT in 2016, Ntsama et al. used vector quantization; Set partitioning in hierarchical trees (SPIHT), and arithmetic coding. They discovered that DWT is more effective than DCT. Additionally, they use a hybrid algorithm made up of DWPT and DPCM, and they evaluate the outcomes using the Modified Algorithm of Decomposition (MAD). To increase their compression factor, they continue to work with DWPT and DCT. In 2013, Colince et al. [6] used JPEG2000 to compress EMG signals. Then, in 2014, they used DPCM as a preprocessing technique [4], as well as DWT and DCT to further boost the compression factor. Eddie et al. used multidimensional multiscale parser (MMP) to encode EMG signals and demonstrate the superiority of MMP technique in [9] to compare the performance of wavelet based approach on the basis of CF and PRD. Berger et al. [10, 23] processed the EMG signal with DWT to achieve a compression factor of up to 90% before normalising and quantizing it with a dynamic bit allocation strategy based on KNN. An arithmetic coder is used to encode data at the end. Welba et al. [13, 15] modify DWPT to enable EMG signal compression. In order to quantize the MDWPT coefficients, the USDZQ (Uniform Scalar Dead-Zone Quantizer) is employed. An arithmetic coder is used to do the entropy coding. Melo et al. use JPEG2000, H.264/advanced video coding, and high efficiency video coding (HEVC) algorithms in [14, 16, 19, and 20] for EMG signal compression, but first they pre-process the signal with Euclidean distance sorting (EDS), region-based Euclidean distance sorting (REDS), and segmentation by similarity (SbS) to improve intersegment correlation of the EMG signal. The EZW encoding is used by Norris et al. [22] to demonstrate the trade-off between computational complexity and distortions in reconstructed signals, and it is discovered that EZW compresses the signal with less losses but greater complexity. Said et al. apply a deep learning strategy in [24] to compress and classify multimodal data. They employ a custom stack auto encoder to extract high level abstraction for intra-correlation of the data. To mimic data inter correlation, a joint layer is placed on top of each encoding component of the stacked auto encoders.

EMG data compression has been the subject of countless studies in the past. A researcher uses a specific process and comes to some conclusions in order to address a research problem (theory, action, or application). The same theory may or may not be supported by published or unpublished results. Since meta-analysis is a well-tested and trustworthy method for systematically examining the outcomes of the studies mentioned above, it is a good choice for capturing research findings in other investigations. This paper performed meta-analysis of published and unpublished studies to determine which studies are more pertinent with regard to compression factor (CF) and percentage root mean square difference (PRD). The results of prior investigations are combined in a methodical and statistical process known as meta-analysis, which identifies patterns and relative behaviors among many studies as well as common solutions.

Forest plots and funnel plot can be used to show the analysis. The findings of the meta-analysis are shown graphically here along with the effect size, confidence level, and degree of prediction. Funnel plot displays sample size and its impact. As a result, smaller research is dispersed near the bottom of the chart, while larger studies are visible at the top. This graph has symmetry in an unbiased study.

EMG data compression has not yet been the subject of a review study. Hence, a symmetry review of EMG compression techniques is required. Thus, this article presents a systematic review. In this study, published and unpublished studies are subjected to meta-analysis to determine which ones are more significant in terms of CF and PRD.

The paper is organized as methodology is presented in Section 2, and the results are presented in Section 3. Section 4 gives the discussion, while Section 5 concludes the study.

2. Methodology

A systematic and statistical process called meta-analysis collects the findings of prior research and offers a common answer as well as trends and comparative behaviors among the various investigations. Forest plot findings include confidence level, prediction level, and effect size. By employing prediction levels, which are usually larger than confidence levels, one can identify the range within which a single result may fall and so represent the accuracy of an estimate. The purpose of effect size is to show how closely the variables are correlated. Another scatter plot that shows the sample size and its impact is a funnel plot. Small studies are thus dispersed across the plot, but large studies are located towards the tip. This plot is symmetrical for objective studies.

For this effort, 24 research works that were published in recognized journals were taken into account. Every sample in every research provided CF and PRD. The average of all CF and PRD out of each literature review were incorporated into this work (as shown in Table 1). To ascertain the relationship among these two variables, the correlation between CF and PRD is performed. Only these two were selected since CF and PRD are important parameters for biological signal compression and are closely interrelated. Lastly, according to the data from the earlier sections, funnel plots have been displayed for further research.

3. Results

For this research, performance measurement metrics like CF and PRD are used. The average value of CF and PRD, the number of samples from each study included in this research, and the correlation between CF and PRD are all displayed in Table 1. Because CF and PRD are both dependent variables, a data sheet for meta-essential correlation is used [25, 26, 27].

Table 2 lists the parameters needed for forest and funnel plots, such as correlation, confidence interval boundaries, and standard error. The Forest Plot is shown in visual form in Figure 1. The Forest plot's last row shows the CI and PI. According to the forest plot, the combined impact sizes for upper and lower CI are 0.81 and 0.73, while the combined impact sizes for upper and lower PI are 0.84 and 0.68. Funnel plot are displayed in Figure (2). The findings of the Funnel Plot analysis indicate that the I^2 heterogeneity is 24.36%.

The Compression Factor (CF) is defined as

$$CF = \frac{EMG_{orig} - EMG_{com}}{EMG_{orig}} \times 100\%$$

Where EMG_{orig} and EMG_{com} are the original and compressed file sizes respectively [21].

Percentage root mean square difference (PRD) is calculated as

$$PRD = \frac{\sqrt{\sum_{n=1}^{k} \left(EMG_{org}[n] - EMG_{rec}[n]\right)^2}}{\sqrt{\sum_{n=1}^{k} \left(EMG_{org}[n]\right)^2}}$$

Where $EMG_{org}[n]$ the original signal and $EMG_{rec}[n]$ is the reconstructed signal and k is the size of EMG signal [21].

4. Discussion

Results of EMG signal compression were examined in this paper utilizing meta-analysis. It is important to demonstrate the consistency of the results achieved and the relationships between the various data compression methods.

When a random effect model with a 95% confidence level was used to examine 21 different research works that were carried out throughout the course of the past 20 years, 13.86% heterogeneity (I^2) showed that all of the research works belonged to the same group.

The cumulative correlation value of the examined studies is 0.77, which shows the overall effect, based on the correlation value (r) used to categorize all 21 research papers with a correlation range of ($0.61 \leq r \leq 0.94$), as shown in Table 1-2. Table 2, included Correlation, Confidence Interval (CI) upper limit, CI lower limit, Weight %, Correlation z and Standard error.

The two main results of a forest plot are the confidence interval (CI) and prediction interval (PI). Upper and lower CI have a combined impact size of 0.81 and 0.73, whereas upper and lower PI had a combined effect size of 0.84 and 0.68. The analysis's findings indicate that the technique is a more reliable one for future investigations if the correlation between the CF and PRD is precisely 0.77.

Figure 1 illustrates a forest plot. In Figure 1, each bullet's size is inversely correlated with its weights, which in turn depend on the sample size. The greatest weight from Figure 1 for Melo et al. 2016 [16] is 12.37% (Table 2), and for that investigation, 80 samples were obtained (Table 1). The author of [16] employs a 2D technique based on a multidimensional multiscale parser (MMP). They also use signal preprocessing to improve intra- and intersegment correlations with segmentation by similarity (SbS), and ultimately use various image and video encoders such as high efficiency video coding (HEVC), H.264/AVC, and JPEG2000.

The effect sizes of studies and standard errors are displayed on the horizontal and vertical axes, respectively, in the funnel plot. It is frequently used to assess publication bias in meta-analyses. An uneven funnel plot in a meta-analysis is typically the result of missing studies brought on by publication bias. It can be seen that there is no publication bias from a symmetrical funnel plot. Figure 2 shows a funnel plot. The findings of the analysis indicate heterogeneity (I^2) for 24.36%.

According to the calculated values, the observed upper and lower confidence intervals are 1.11 and 0.93, respectively. To achieve better symmetry, the upper and lower CI must be adjusted using the trim and fill method, which supposes that the studies with the largest magnitudes of effect sizes in the opposite trend are curbed. As a result, with the imputed 3 studies [12, 20 and 14], the adjusted upper and lower CI are 1.08 and 0.91, respectively. The corrected upper and lower PI are 1.26 and 0.73, respectively, from the observed values of 1.22 and 0.83.

5. Conclusion

This research uses meta-analysis to identify the most appropriate EMG compression and reconstruction method. Since homogeneity can be seen in all 21 publications for analysis. The correlation among CF and PRD is the basis for the analysis. A research's relevance is determined by its weights (as shown in table 2), with the research having the highest weight in that analysis being the most significant. Based on the study, it has been determined that the de Melo WC (2016) used a two-dimensional approach for EMG compression. They specifically used a recurrent pattern matching algorithm known as MMP. The study by researcher is the most significant process for correlating PRD and CF values. It may also be concluded from a meta-analysis of 21 research studies that CF and PRD correlation can be used to validate future EMG compression and reconstruction efforts.

The following critical factors must be taken into account in order to define future directions for EMG signal compression and to promote ongoing research efforts. Sensitivity, correlation, and accuracy are just a few of the considerations that comparisons take into account.

Table 1 Data of EMG Compression Methods from Literature Review

S. No.	Authors	**Technique used in Paper**	Correlation	CF Mean	PRD Mean	No. of samples
1	Francisco A.O. Nascimento et al. 2021 [12]	Improved two-dimensional dynamic S-EMG Signal compression with robust automatic segmentation	0.91	82.50	3.29	6
2	Colince Welba et al. 2020 [13]	Contribution to S-EMG signal compression in 1D by the combination of the modified discrete wavelet packet transform (MDWPT) and the discrete cosine transform (DCT)	0.61	91.97	7.01	48
3	Vibha Aggarwal et al. 2019 [21]	Quality Controlled EMG Signal Compression using Linear and Non Linear Transforms.	0.35	88.95	3.03	95
4	Khalid M.Hosny et al. 2018 [1]	Efficient compression of bio-signals by using Tchebichef moments and Artificial Bee Colony.	0.77	74.17	4.63	9
5	Marcel H. Trabuco et al. 2017 [11]	S-EMG signal compression in one-dimensional and two-dimensional approaches.	0.81	84.79	6.01	24
6	Ahmed Ben Said et al. 2017 [24]	Multimodal deep learning approach for joint EEG-EMG data compression and classification.	0.64	50.00	12.78	9

7	Eloundou Pascal Ntsama et al. 2016 [2]	Comparison study of EMG signals compression by methods transform using vector quantization, SPIHT and arithmetic coding	0.58	62.52	0.47	84
8	Aimé Joseph Oyobé-Okassa et al. 2016 [3]	Compression of EMG Signals by a Hybrid Algorithm Composed of DWPT and DPCM	0.23	72.65	2.60	29
9	C. Welba et al. 2016 [15]	Compression of electromyography signals by the packet transform modified wavelets	0.81	80.78	2.38	21
10	Wheidima Carneiro de Melo et al. 2016 [16]	SEMG signal compression based on two-dimensional techniques.	0.76	82.50	6.40	80
11	Aimé Joseph Oyobé-Okassa et al. 2016 [17]	Compression of EMG Signals by Superimposing Methods: Case of WPT and DCT.	0.70	73.62	2.40	20
12	Wheidima Carneiro de Melo et al. 2016 [19]	Electromyographic signal compression through image encoders and preprocessing techniques.	0.87	80.00	3.62	45
13	Wheidima C. de Melo et al. 2015 [20]	Electromyographic signal compression based on two-dimensional techniques.	0.88	82.50	4.20	24
14	Welba Colince et al. 2014 [4]	Exploitation of differential pulse code modulation for compression of EMG signals by a combination of DWT and DCT	0.69	83.72	0.41	22
15	Marcel Henrique Trabuco et al. 2014 [5]	S-EMG signal compression based on domain transformation and spectral shape dynamic bit allocation.	0.81	84.08	7.92	46
16	Ntsama Eloundou Pascal et al. 2013 [6]	Evaluation of EMG signals compression by JPEG 2000 called 1D.	0.66	61.37	0.60	57

17	M. H. Trabuco et al. 2013 [18]	Compression of S-EMG signals by transforms and spectral profile for bit allocation	0.78	82.98	5.96	14
18	Wheidima C. Melo et al. 2012 [14]	Electromyographic signal compression based on preprocessing techniques.	0.94	82.50	3.82	8
19	Marcus V. C. Costa et al. 2009 [7]	Two-dimensional compression of surface electromyographic signals using column-correlation sorting and image encoders	0.85	82.74	8.25	31
20	Marcus Vinicius Chaffim Costa et al. 2008 [8]	Compression of electromyographic signals using image compression techniques.	0.79	82.50	6.13	8
21	Eddie B. L. Filho et al. 2008 [9]	On EMG signal compression with recurrent patterns	0.82	77.50	4.48	8
22	Pedro de A. Berger et al. 2007 [10]	A new wavelet-based algorithm for compression of EMG signals.	0.72	75.24	6.50	21
23	Pedro de A Berger et al. 2006 [23]	Compression of EMG signals with wavelet transform and artificial neural networks.	0.83	77.50	7.59	16
24	J.A. Norris et al. 2001 [22]	Steady-state and dynamic myoelectric signal compression using embedded zero-tree wavelets.	0.72	77.50	18.13	64

Table 2 Subgroup Analysis of ECG Compression Methods

S. No.	Author	Correlation	CI Lower limit	CI Upper limit	Weight	Correlation (z)	Standard error (z)
		Forest Plot Calculation				**Funnel Plot Calculation**	

1	Francisco A.O. Nascimento et al. 2021 [12]	0.91	0.06	1.00	0.72%	1.54	0.58
2	Colince Welba et al. 2020 [13]	0.61	0.38	0.76	8.42%	0.70	0.15
3	Khalid M.Hosny et al. 2018 [1]	0.77	0.07	0.96	1.41%	1.01	0.41
4	Marcel H. Trabuco et al. 2017 [11]	0.81	0.59	0.92	4.49%	1.13	0.22
5	Ahmed Ben Said et al. 2017 [24]	0.64	-0.18	0.94	1.41%	0.76	0.41
6	C. Welba et al. 2016 [15]	0.81	0.57	0.93	3.92%	1.13	0.24
7	Wheidima Carneiro de Mel et al. 2016 [16]	0.76	0.65	0.84	12.37%	1.00	0.11
8	Aimé Joseph Oyobé-Okassa et al. 2016 [17]	0.70	0.34	0.88	3.72%	0.87	0.24
9	Wheidima Carneiro de Melo et al. 2016 [19]	0.87	0.77	0.93	7.99%	1.33	0.15
10	Wheidima C. de Melo et al. 2015 [20]	0.88	0.72	0.95	4.49%	1.36	0.22
11	Welba Colince et al. 2014 [4]	0.69	0.36	0.87	4.11%	0.85	0.23
12	Marcel Henrique Trabuco et al. 2014 [5]	0.81	0.67	0.89	8.13%	1.12	0.15
13	Ntsama Eloundou Pascal et al. 2013 [6]	0.66	0.48	0.79	9.66%	0.79	0.14

14	M. H. Trabuco et al. 2013 [18]	0.78	0.38	0.94	2.50%	1.05	0.30
15	Wheidima C. Melo et al. 2012 [14]	0.94	0.62	0.99	1.18%	1.78	0.45
16	Marcus V. C. Costa et al. 2009 [7]	0.85	0.71	0.93	5.75%	1.27	0.19
17	Marcus Vinicius Chaffim Costa et al. 2008 [8]	0.79	0.00	0.97	1.18%	1.06	0.45
18	Eddie B. L. Filho et al. 2008 [9]	0.82	0.09	0.98	1.18%	1.15	0.45
19	Pedro de A. Berger et al. 2007 [10]	0.72	0.40	0.89	3.92%	0.91	0.24
20	Pedro de A Berger et al. 2006 [23]	0.83	0.54	0.95	2.92%	1.20	0.28
21	J.A. Norris et al. 2001 [22]	0.72	0.57	0.82	10.55%	0.90	0.13
	Combined effect size	0.77	0.73	0.81		1.02	0.04

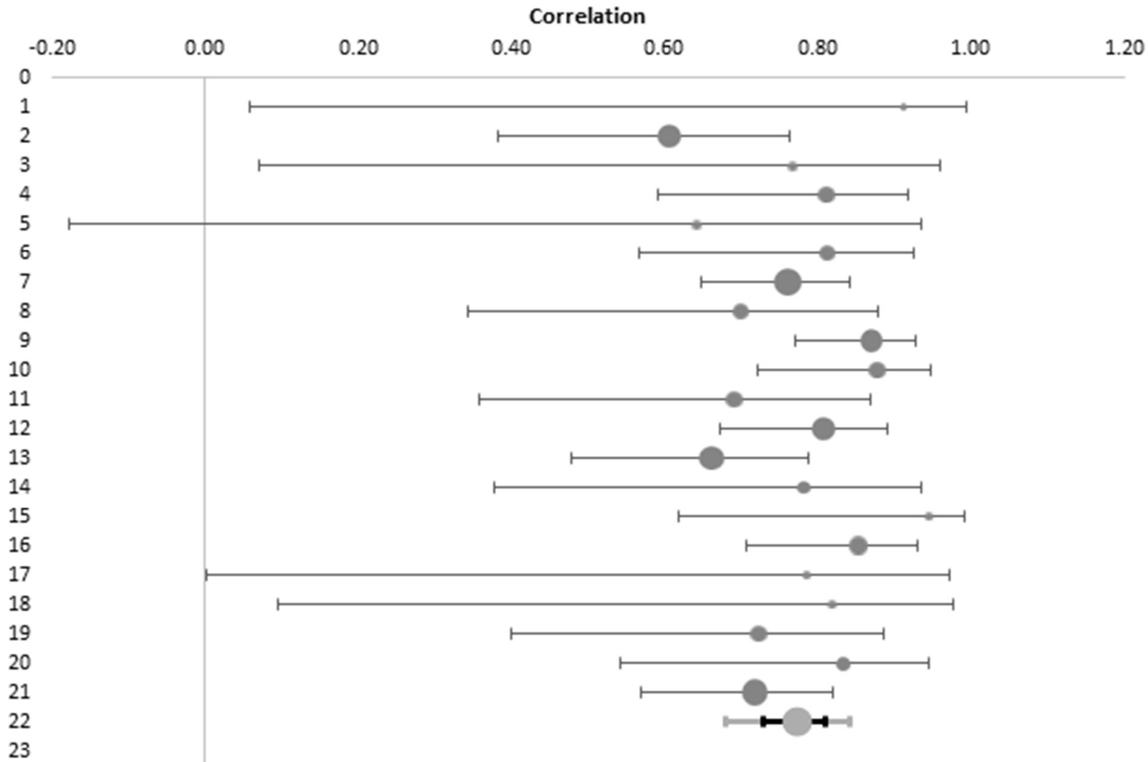

Figure 1 Forest Plot

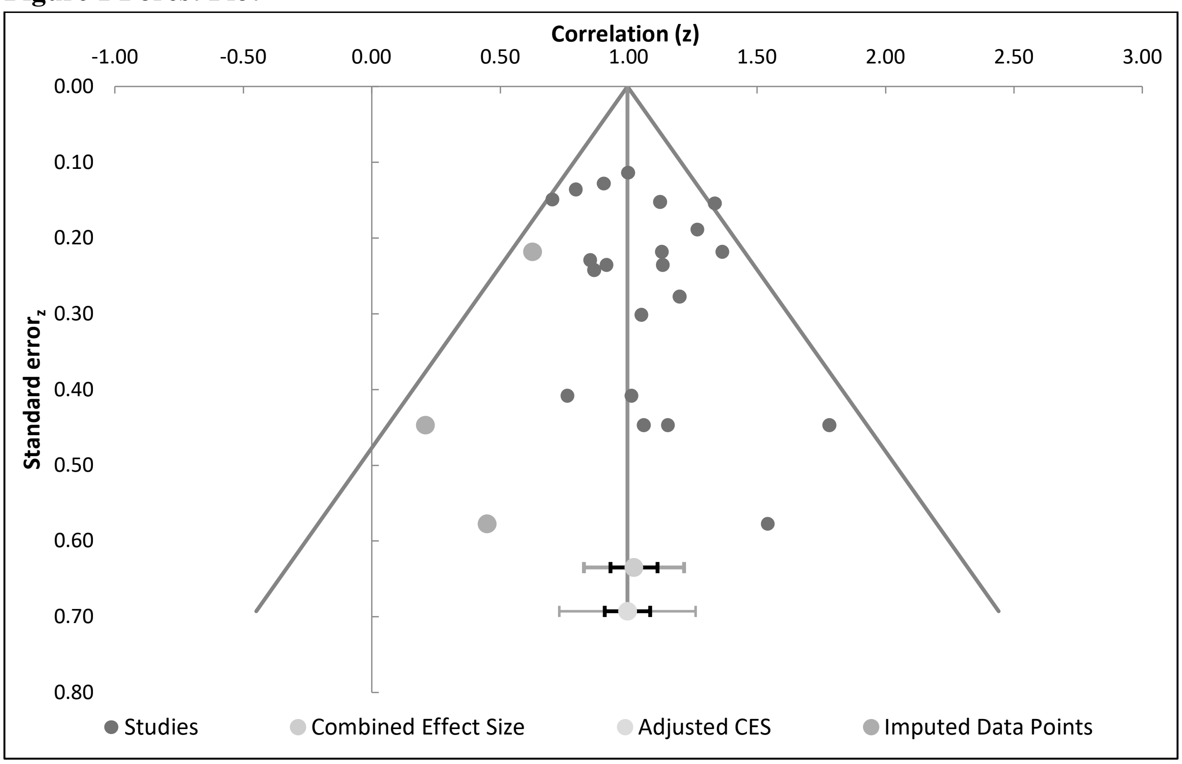

Figure 2 Funnel Plot

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