Autoscore: An R package for scoring orthographic transcripts for research and the clinic

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Abstract

Autoscore is an open-source research and clinical tool to score orthographic listener transcripts. It has previously been demonstrated that Autoscore is highly efficient and accurate. Herein, we present the design of the Autoscore package, show how the software can be extended or improved, and provide a brief tutorial on the use of the package on example data. We conclude by discussing the implications of Autoscore and other openly accessible tools like it in improving replicability and reproducibility of research.

Behavioral research often relies on human tasks for scoring and coding the data. For example, video and audio data often need to be assessed by trained researchers to obtain qualitative and quantitative information about behaviors and social interactions. These tasks can be essential for the research but can also be costly—both in terms of effort, time, and resources. Problematically, though, these tasks also can reduce the ability to replicate and reproduce scientific results due to problems associated with scoring fatigue (which introduces

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otherwise avoidable errors), the difficulty of gauging the accuracy of the human-performed task (mistakes are often unpredictable without cumbersome double scoring procedures), and the time, cost, and effort necessary to score accurately.

Well-designed automation tools can alleviate many scoring and coding issues, as these tools do not experience scoring fatigue, they require very little time to produce the results (often seconds instead of days), and the mistakes can be few, predictable, and can be minimized. In fact, researchers have relied on the automation of many tasks via various tools across the behavioral sciences (Boersma, 2001; Borja-Cacho & Matthews, 2008; Borrie, Barrett, & Yoho, 2019; Hillenbrand & Gayvert, 2005; Silge & Robinson, 2017). However, the development of such automation tools can have upfront costs, including the actual development, the validation and testing, the documentation, and the release of the software. Because of this, some labs have used "in-house" software, resorting to only develop and test it but not release the tool in any fashion publicly. Unfortunately, this only helps reduce costs and effort for studies produced by that lab and it makes it difficult for other research teams to confidently replicate the work.

As science becomes more focused on reproducible and open results (e.g., "Center for Open Science: Mission," 2019; Foster & Deardorff, 2017; Nosek et al., 2015), it is valuable to offer these tools in some form publicly. Benefits for the researchers providing the tool are plentiful. For example, by releasing the software openly, it can benefit from the vast skills and knowledge of the general research community. This allows for errors to be fixed, improvements in speed and accuracy to be made, and extensions to be added. Even in cases where the software code is not released openly (for a number of valid reasons), having an accessible tool that other researchers can use to replicate results is important.

Herein, we describe an open-source tool known as autoscore that automates the task of scoring orthographic listener transcripts. This task was an important candidate to automate as this task has well-defined, objective scoring guidelines, it is done repetitively requiring human effort and time, and is found in various fields and clinics (Bent, Baese-Berk, Borrie, &

McKee, 2016; Bradlow & Bent, 2008; Cooke et al., 2013; Davis, Johnsrude, Hervais-Adelman, Taylor, & McGettigan, 2005; Guediche, Fiez, & Holt, 2016; Healy, Yoho, Wang, & Wang, 2013; Hustad, 2006; Liss, Spitzer, Caviness, Adler, & Edwards, 1998; Luce & Pisoni, 1998; Munro, 1998; Rønne, Laugesen, & Jensen, 2017; Tye-Murray, Sommers, & Spehar, 2007; Van Engen, Phelps, Smiljanic, & Chandrasekaran, 2014). This task often includes a target word or phrase produced by an individual while a listener is required to repeat back the word or phrase that they heard, or perceived, while an assistant writes down the response (Tikofsky & Tikofsky, 1964; Yorkston & Beukelman, 1980). What is often obtained from this task is information about how well the response word or phrase—the word or phrase perceived by the listener—matches the target word or phrase. It has been used to understand word recognition in speech disorders (Borrie, Lansford, & Barrett, 2017, 2018; Hustad, 2006), to gauge the benefits of certain interventions (Healy et al., 2013), and to assess hearing loss (Huttunen & Sorri, 2004). Although used in several areas, it could be further adopted by other research and clinical areas as part of their surveys and assessments. The lack of adoption is likely increased by the effort required to score the listener transcripts in a timely and accurate fashion.

Previously, Autoscore was shown to increase efficiency and improve accuracy (Borrie et al., 2019). Results indicated that the tool was fast (taking seconds instead of the hours it took human scorers) and was highly accurate. The accuracy for two in-house data sets were each above 99%. Autoscore was over 95% accurate on an externally-provided data set and could have achieved over 98% with more of the scoring rules in place. Across the data sets, humans were similarly accurate, generally around 98% correct. However, an important difference between Autoscore and human scorers is that the errors committed by Autoscore are predictable and confined whereas the errors by human scorers were less predictable and far broader. Overall, the study concluded that Autoscore is just as accurate or more accurate than human scorers and much faster.

To help researchers use the tool and adapt it for their needs, we discuss the design of

Autoscore as written in the R programming language (R Core Team, 2018), its implementation of the scoring rules, and provide concrete steps for others to extend and/or improve the tool. We further demonstrate its use with a short tutorial. We conclude by discussing how the tool and others like it can help improve replicability and reproducibility of research.

Design of Autoscore

The initial release of the `autoscore` package was built in R version 3.5.1 and relies on a number of valuable R packages: `stringr`, `dplyr`, `knitr`, `purrr`, `tidyr`, `tm`, `tibble`, `magrittr`, `crayon`, and `cli` (Bache & Wickham, 2014; Csárdi, 2017, 2018; Feinerer, Hornik, & Meyer, 2008; Henry & Wickham, 2018; Müller & Wickham, 2018; Wickham, 2018; Wickham et al., 2018; Wickham & Henry, 2018; Xie, 2015).

The autoscore package was designed with the possibility of additional scoring rules to be included at the forefront. The various needs of different fields made it clear that the rules first implemented were unlikely to be the only ones integrated into the system. As such, each scoring rule (or group of scoring rules) has its own function that is included in the overall pipeline that ultimately is called by the `autoscore()` function. This means that new rules can be inserted into the pipeline with minimal disturbance to the current functionality of the tool. We outline concrete steps to adjust autoscore later on.

Figure 1 presents a diagram of the main function `autoscore()`. This function combines all the sub-functions, including the implementations of the scoring rules, and applies these sub-functions to the input (i.e., the data and the scoring rules chosen). As such, this main function constructs the overall pipeline of the scoring. This function outputs the original data with an additional column providing the counts of the correct responses. When the original data has a column named `human` with human scored counts, Autoscore will also include a column indicating if the human and Autoscore counts match up (true or false). Using `autoscore()` with another function called `pwc()` will produce the PWC for each line of the original data as well.

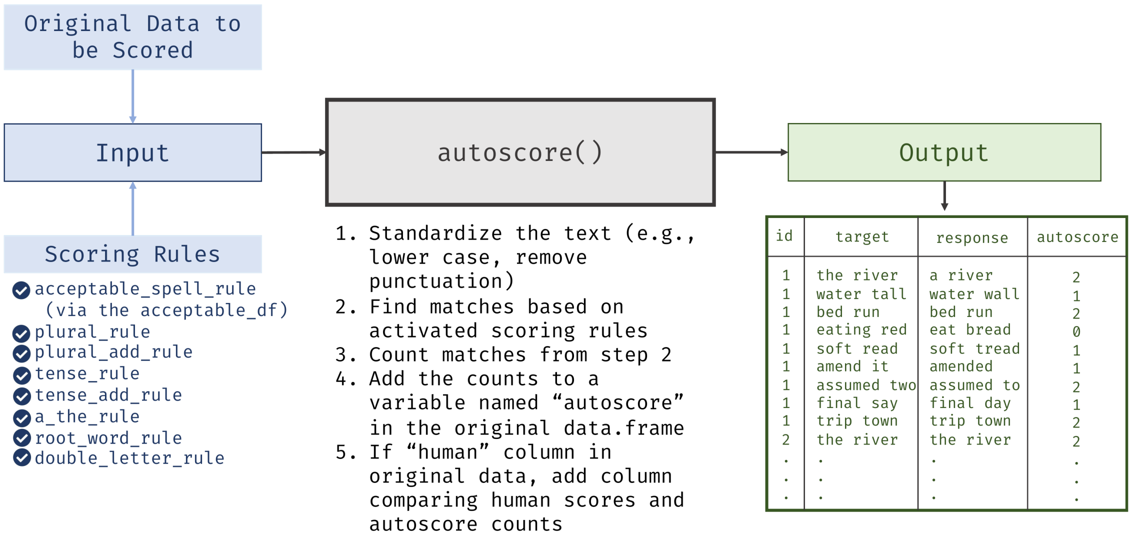

Figure 1. A diagram of the main function `autoscore()`, showing the inputs of both the original data and selected scoring rules, the steps taken by Autoscore to score the transcripts, and the data output.

Scoring Rules

A major benefit of using Autoscore is the flexible use of scoring rules—rules that dictate what is counted as a correct response and what is not. At its simplest, scoring can be done based on an exact match wherein even spelling mistakes can be overlooked. With more rules in place, Autoscore can adjust for plural and tense differences, can use a custom list of “acceptable spellings,” among others. The current list of scoring rules are shown below, categorized as either a spelling or grammar rule.

Spelling Rules.

1. *Acceptable Spelling Rule.* This rule allows the researcher to add a custom list of acceptable spellings for target words in the corpus. A default list is provided with the package that currently includes over 300 acceptable spellings. A researcher may use the default, provide additional acceptable spellings to this default list, or provide a novel list specific to the corpus being used.
2. *Root Word Rule.* When this rule is applied, the response word is counted correct if the target word (e.g., day) is embedded at the beginning of the word (e.g., daytime).

3. *Double Letter Rule.* This rule corrects for a common misspelling, that of an accidental double letter (e.g., "thee" instead of "the") or an omission of a necessary double letter (e.g., "atack" instead of "attack").

Grammar Rules.

1. *Tense Rule.* This rule allows additions or omissions in the response of the suffix "-d" or "-ed". It is termed the "tense rule" although it will count additions or omissions of any -d or -ed suffixes (e.g., "seed" for "see").
2. *Tense+ Rule.* This rule, similarly to the Tense Rule, deals with the suffix "-d" or "-ed" but only allows the addition (not the omission) of the suffix.
3. *Plural Rule.* This rule allows additions or omissions in the response of the suffix "-s" or "-es". Similar to the Tense Rule, it is termed the "plural rule" although it will count additions or omissions of any -s or -es suffixes (e.g., "jumps" and "jump").
4. *Plural+ Rule.* This rule, similarly to the Plural Rule, deals with the suffix "-s" or "-es" but only allows the addition (not the omission) of the suffix.
5. *A-The Rule.* This rule allows instances of "the" to match instances of "a".

These scoring rules can seem overly flexible. For example, the tense rule can score "seed" and as a correct response to "see". However, in many cases, this fits the pronunciation of the word and therefore makes sense in many research and clinic domains to allow it to be scored as correct.

Of course, each situation can require novel scoring rules that are not currently implemented in Autoscore. In such cases, a researcher has two options: 1) include the new scoring rule as part of the acceptable spelling list or 2) make custom adjustments to the source code of Autoscore. For the first option, it can be applied by a visual assessment of the words in the corpus that would be affected by the new scoring rule; an addition of the affected words to the acceptable spellings column in the acceptable spelling list; and use of that list in conjunction with, or in place of, the Acceptable Spelling Rule.

For example, we may want to initiate a new scoring rule that allows all 'c' and 'k' to be interchangeable given their identical phonemes in many situations. Using the Acceptable Spelling Rule, we can assess the places where ‘c’ or ‘k’ could be interchanged in the target corpus and add those to the list with the associated target words. Words in the target list such as “clown” and “call” could be affected. We could add “klown” and “kall” to the acceptable spelling list. Then, Autoscore would do the scoring with this updated list.

For fairly straightforward rules that are only needed occasionally, this first option is likely best. For other situations, those with rules that are needed more often across different target corpora, we recommend the second option, that of adjusting the source code of Autoscore to fit the needs of the project. This option is discussed further in the next section.

Steps to Extend/Improve Autoscore

The Autoscore package is housed on GitHub, a “hub” for code repositories. The use of GitHub is explained elsewhere (see https://guides.github.com//git-handbook/). For our purposes, it is important to know that GitHub allows one to copy the source code of a project, make changes within their own copy of the project, and then (optionally) request that the changes be integrated into the main project.[1] Although it is not necessary to use GitHub, we recommend it as it eases several of the steps below.

To extend/improve the Autoscore package, consider the following steps.

1. Decide what needs to be integrated or changed. This change must be clearly defined to put it reliably into the code.
2. “Fork” or copy the Autoscore package from github.com/autoscore/autoscore. All changes can be made to this copied version of the package.
3. Make adjustments to the code (see example of adding or adjusting rule below) and run

[1] It is important to note that not all projects on GitHub can be treated the same. Before making any changes to any code, it is important to always check the license for its use and adjustment. For example, Autoscore uses the GPL-3 as described in the LICENSE file. Additionally, some projects have a Code of Conduct agreement that, once an individual begins working with the source code, agrees to adhere to. For example, Autoscore has a Code of Conduct that prohibits any type of harassment.

tests on the new code to make sure it is accurate and does not break the functionality of any rules that are needed.

4. If the rule may benefit more than a single lab or clinic, send a "pull request" that sends a message requesting the adjustments be included in the main Autoscore package. In this request, it is best if it is shown that all the rules work as they did previously (unit tests are included in the package for researchers to use).

Steps 3 and 4 can be done many times, if needed.

Adding or Adjusting a Rule

To clarify the process, we highlight how one might add an extra rule to Autoscore. As mentioned earlier, each new rule can be included as its own function. If we return to our fictitious rule regarding 'c' and 'k', we can integrate this into the source code. Using GitHub, we can fork (copy) the repository into our account. We now can make changes to this code, document the changes, and test it out. Once it is working, we can perform a "pull request"—a request for the newly integrated code to be inserted into the main Autoscore package.

Prior to the rules being implemented in the pipeline of Autoscore, the target phrases are split into individual words and all punctuation is removed. This is then passed to a function that allows the scoring functions to look at individual phrases. That means, any new scoring rule function needs to accept a character vector of single words (e.g., `c("this", "is", "a", "phrase")`) and a logical argument indicating whether the rule is activated.

The following example function, when the rule is activated (the `use` argument), will replace all instances of 'k' with 'c'. This general structure of a new rule will work well within Autoscore.

```
new_scoring_rule <- function(chr, use) {
  if (isTRUE(use)){
    chr <- stringr::str_replace_all(chr,
                                    pattern = "k",
```

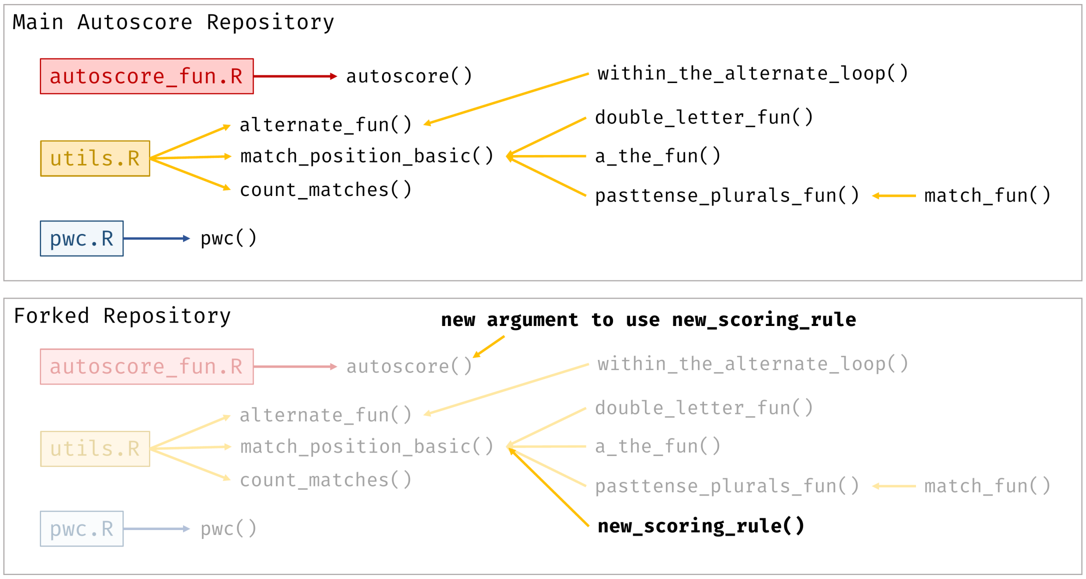

Figure 2. A diagram showing the main autoscore files and functions from the "Main Autoscore Repository" and how, by copying–or forking–the main repository, one can add a new function; in this case, called `new_scoring_rule()`. Although not shown, the individual could request that the new function get integrated in the main repository or remain in that single “forked" version for use in a single group or lab.

```
                                        replacement = "c")
    names(chr) <- chr
    chr
  } else {
    chr
  }
}
```

As shown in Figure 2, this new function can be included in the pipeline inside of the `match_position_basic()` function. With the added argument to the `autoscore()` function to allow a user to specify the use of the new scoring rule, Autoscore will be able to integrate the new rule with minimal changes to the overall functionality of the package.

The Use of Autoscore

Autoscore, at its most basic, can be used with a single data set without any additional arguments or steps needed. The only requirements for it to do the default scoring is a data set with variables with the names of `id`, `target`, `response`, and (optionally) `human`. These can be in any order and any case (e.g., `ID`, `Id` and `id` are all valid). For this short tutorial, we will use a data set provided in the package.

```
library(autoscore)  ## attach the package
example_data        ## initiate the example data set
```

```
# A tibble: 40 x 4
      Id Target                      Response                    human
   <dbl> <chr>                       <chr>                       <dbl>
 1     1 mate denotes a judgement    made the dinner in it           1
 2     1 rampant boasting captain    rubbed against the captain      1
 3     1 resting older earring       resting alert hearing           1
 4     1 bolder ground from justice  boulder down from dresses       2
 5     1 remove and name for stake   remember the name for steak     3
 6     1 done with finest handle     dinner finished handle          1
 7     1 support with dock and cheer she put the duck in chair       1
 8     1 or spent sincere aside      earth bent spent her aside      2
 9     1 account for who could knock i can for hookah knock          2
10     1 connect the beer device     connected beard kindle bus      1
# ... with 30 more rows
```

This shows the first few lines of the data set. We have a unique identifier for each participant (although all that is shown is the ID of 1). It further contains a target phrase with a corresponding response phrase. Finally, this data set had a research assistant score each of the phrases, which is included in the `human` column.

With this data set, we can use the defaults of Autoscore by just providing it to the function `autoscore()`. The output is similar to the initial data set except there are two additional columns: `autoscore` and `equal`. That is, no columns are removed or altered in the calculation. The new `autoscore` column presents the counts of correct responses for each target phrase while the new `equal` column presents whether the human and Autoscore agreed. Notably, the `equal` column only appears when there is a `human` column in the data set.

For this example, only two instructive rows are shown even though all rows were scored and the `id` column is not shown, due to space. The specific rows were chosen to highlight nuances of the scoring.

```r
autoscore(example_data)    ## autoscore with all defaults
```

```
# A tibble: 2 x 5
  target                     response                  human autoscore equal
  <fct>                      <fct>                     <dbl>     <int> <lgl>
1 bolder ground from justice boulder down from dress~     2          1 FALSE
2 attend the trend success   attended trend success       3          2 FALSE
```

By default, no scoring rules are implemented. In the example above, the rows show disagreements between the human scorer and autoscore. This is due to the homophone of "bolder" and "boulder" and the tense of "attend" and "attended". This can be fixed using the *acceptable spellings rule* and the *tense rule* that will be highlighted next.

Returning to the first row of the output, we see a need for adjusting for potential homophones (e.g., bolder and boulder). As explained before, the acceptable spellings rule allows researchers to use the default list of acceptable spellings, include their own, or combine their own with the default list. For the following example, we will rely on the default list.

```r
autoscore(example_data,
          acceptable_df = autoscore::acceptable_spellings,
          tense_rule = TRUE)
```

```
# A tibble: 2 x 5
  target                     response                  human autoscore equal
  <fct>                      <fct>                     <dbl>     <int> <lgl>
1 bolder ground from justice boulder down from dress~     2          2 TRUE
2 attend the trend success   attended trend success       3          3 TRUE
```

Now, because the homophones "bolder" and "boulder" are included in the default list, Autoscore recognizes that bolder and boulder are homophones and therefore boulder should be counted as a correct response. This default list contains a number of common homophones and other common misspellings but will not catch all present in every English corpus. As such, it is recommended that a researcher assess their individual corpus for words that could have obvious misspellings or homophones.

It is also possible to adjust whether the automatic rules are activated as shown below. In the following example, we use the plural+, tense+, and root word rules in addition to using the default acceptable spellings list.

```
autoscore(example_data,
          acceptable_df = autoscore::acceptable_spellings,
          plural_add_rule = TRUE,
          tense_add_rule = TRUE,
          root_word_rule = TRUE)
```

```
# A tibble: 2 x 5
  target                     response                 human autoscore equal
  <fct>                      <fct>                    <dbl>     <int> <lgl>
1 bolder ground from justice boulder down from dress~     2         2 TRUE
2 attend the trend success   attended trend success       3         3 TRUE
```

For these specific rows, there is no change as our rule adjustments do not impact either of these rows. Even though it may seem as though "attended" could be impacted, it actually fits the tense+ rule nicely (it adds a tense and does not omit one).

Finally, the function `pwc()` provides the actual percent words correct per `id`. This function takes the output from `autoscore()` and calculates the PWC per `id` using:

$$\frac{\text{total number of correct responses}}{\text{total number of target words}} \times 100.$$

Here, we can obtain the average for each ID in the example data set, where the first individual had 36.5% accuracy while individual 2 had 20.8% accuracy. Note that the `id` variable name will be lower case in the output of of the data frame produced by `autoscore()`.

```
scored <- autoscore(example_data,
                    acceptable_df = autoscore::acceptable_spellings,
                    plural_add_rule = TRUE,
                    tense_add_rule = TRUE)
pwc(scored, id)
```

```
## # A tibble: 2 x 2
##      id   pwc
##   <dbl> <dbl>
```

```
## 1      1  36.5
## 2      2  20.8
```

This approach is entirely reproducible and reduces risk for scoring and analysis errors. Within the same program, one can clean, score, and assess listener transcripts, potentially in just a few lines of code. Furthermore, these analyses can be provided to other researchers that they may replicate exactly the steps used in analyzing the data.

Discussion

Open-source tools for research and clinical use can increase efficiency and effectiveness of science and care. They have provided incredible functionality to many fields across the sciences, aiding in measuring, accessing, cleaning, and analyzing data. However, there is more work to be done on both novel tools and existing ones (Hillenbrand & Gayvert, 2005). Herein, we have described one of those tools designed specifically for the communication sciences.

Automated tools in the communication sciences are not new (see Llisterri (2018) for an extensive list of accessible tools), even when it comes to scoring orthographic listener transcripts (Borja-Cacho & Matthews, 2008). Many tools, however, are not released to the public. Individuals do not release code as open-source for various reasons, including privacy, proprietary rights, the effort required to get tool in a good enough condition for public release, future use of the tool for funding opportunities, the difficulty of maintaining an open-source tool, questions regarding copyright, among others. These purposes are important and should not be overlooked nor discounted. However, in situations where it is possible, releasing the tool as an open-sourced package for others to use, improve, and extend can increase the likelihood that the tool will reach and benefit a broader audience. We recommend, as Nosek et al. (2015), that any use of open-sourced software be cited properly to provide further incentive for researchers to release their tools to the public.

Beyond the benefits of increased efficiency, tools like Autoscore also can remove an item in the long list of researcher decisions that cannot be adequately documented. Researchers have several, often nuanced, decisions that can greatly impact the results (Silberzahn et al., 2018; Wicherts et al., 2016). The problem, however, is not so much in the specifics of the decision, but often the clear documenting of the decision that would allow replication. Tools like Autoscore allow for researchers to concretely show exactly what procedures were used to obtain the results, thereby removing one variable of the "researcher degrees of freedom" (Simmons, Nelson, & Simonsohn, 2011; Wicherts et al., 2016). Less variability between researcher teams can mean more precise, reproduced results.

Integrating Autoscore. One of the benefits of having Autoscore as an open-source software is its ability to be integrated as part of a larger research or clinical program. Although not shown herein, R can be called from various languages (C, C++, Java, etc.) and therefore can be integrated within other software. For example, in a clinical setting it may be important to assess the PWC quickly across various conditions. Instead of requiring a clinician to take time to score it while also caring for a client, Autoscore can be included in the software used to assess the listener's perception of speech, outputting PWC across conditions.

Online Tool. Importantly, an online tool developed in the Shiny framework (Chang, Cheng, Allaire, Xie, & McPherson, 2018) is available for use by individuals without R experience or interests. This aspect of Autoscore, including accuracy and efficiency of the automated scoring, was demonstrated by Borrie et al. (2019). The online tool relies on the `autoscore` R package for functionality. As such, to make changes to the online application, one must make changes to the R package. These changes can eventually be translated into the online tool after proper testing has been done with the new functionality. This online tool is housed on a secure server at Utah State University.

Conclusion

Autoscore is an open-source tool for scoring orthographic listener transcripts. Its design allows for the adjustment, extension, and improvement by other research and clinical teams. As part of the broader mission of open science, we anticipate that it can help increase the replicability of research in its domain.

References

Bache, S. M., & Wickham, H. (2014). *Magrittr: A forward-pipe operator for r.* Retrieved from https://CRAN.R-project.org/package=magrittr

Bent, T., Baese-Berk, M., Borrie, S. A., & McKee, M. (2016). Individual differences in the perception of regional, nonnative, and disordered speech varieties. *The Journal of the Acoustical Society of America*, *140*(5), 3775–3786. doi:10.1121/1.4966677

Boersma, P. (2001). Praat, a system for doing phonetics by computer. *Glot International*, *5*(9/10), 341–345.

Borja-Cacho, D., & Matthews, J. (2008). Impact of sentence length and phonetic complexity on intelligibility of 5 year old children with cerebral palsy. *Nano*, *6*(9), 2166–2171. doi:10.1021/nl061786n.Core-Shell

Borrie, S. A., Lansford, K. L., & Barrett, T. S. (2017). Rhythm Perception and Its Role in Perception and Learning of Dysrhythmic Speech. *Journal of Speech Language and Hearing Research*, *60*(3), 561. doi:10.1044/2016_JSLHR-S-16-0094

Borrie, S., Barrett, T., & Yoho, S. (2019). Autoscore: An open-source automated tool for scoring listener perception of speech. *The Journal of the Acoustical Society of America.*

Borrie, S., Lansford, K., & Barrett, T. (2018). Understanding dysrhythmic speech: When rhythm does not matter and learning does not happen. *Journal of the Acoustical Society of America*, *143*(5). doi:10.1121/1.5037620

Bradlow, A. R., & Bent, T. (2008). Perceptual Adaptation to Non-Native Speech. *Cognition*, *106*(2), 707–729. doi:10.1007/978-1-62703-673-3

Center for Open Science: Mission. (2019). https://cos.io/about/mission/.

Chang, W., Cheng, J., Allaire, J., Xie, Y., & McPherson, J. (2018). *Shiny: Web application framework for r.* Retrieved from https://CRAN.R-project.org/package=shiny

Cooke, M., Mayo, C., Valentini-Botinhao, C., Stylianou, Y., Sauert, B., & Tang, Y. (2013). Evaluating the intelligibility benefit of speech modifications in known noise conditions. *Speech Communication*, *55*(4), 572–585. doi:10.1016/j.specom.2013.01.001

Csárdi, G. (2017). *Crayon: Colored terminal output*. Retrieved from https://CRAN.R-project.org/package=crayon

Csárdi, G. (2018). *Cli: Helpers for developing command line interfaces*. Retrieved from https://CRAN.R-project.org/package=cli

Davis, M. H., Johnsrude, I. S., Hervais-Adelman, A., Taylor, K., & McGettigan, C. (2005). Lexical information drives perceptual learning of distorted speech: Evidence from the comprehension of noise-vocoded sentences. *Journal of Experimental Psychology: General*, *134*(2), 222–241. doi:10.1037/0096-3445.134.2.222

Feinerer, I., Hornik, K., & Meyer, D. (2008). Text mining infrastructure in r. *Journal of Statistical Software*, *25*(5), 1–54. Retrieved from http://www.jstatsoft.org/v25/i05/

Foster, E. D., & Deardorff, A. (2017). Open Science Framework (OSF). *Glot International*, *5*(9/10), 341–345.

Guediche, S., Fiez, J. A., & Holt, L. L. (2016). Adaptive plasticity in speech perception: effects of external information and internal predictions. *Journal of Experimental Psychology: Human Perceptual Performance*, *42*(7), 1084–1059. doi:10.1037/xhp0000196

Healy, E. W., Yoho, S. E., Wang, Y., & Wang, D. (2013). An algorithm to improve speech recognition in noise for hearing-impaired listeners. *The Journal of the Acoustical Society of America*, *134*(4), 3029–3038. doi:10.1121/1.4820893

Henry, L., & Wickham, H. (2018). *Purrr: Functional programming tools*. Retrieved from https://CRAN.R-project.org/package=purrr

Hillenbrand, J. M., & Gayvert, R. T. (2005). Open Source Software for Experiment Design and Control. *Journal of Speech Language and Hearing Research*, *48*(1), 45.

doi:10.1044/1092-4388(2005/005)

Hustad, K. C. (2006). A closer look at transcription intelligibility for speakers with dysarthria: Evaluation of scoring paradigms and linguistic errors made by listeners. *American Journal of Speech-Language Pathology*, *15*(3), 268–277. doi:10.1044/1058-0360(2006/025)

Huttunen, K., & Sorri, M. (2004). Methodological aspects of assessing speech intelligibility among children with impaired hearing. *Acta Oto-Laryngologica*, *124*(4), 490–494. doi:10.1080/00016480310000557

Liss, J. M., Spitzer, S., Caviness, J. N., Adler, C., & Edwards, B. (1998). Syllabic strength and lexical boundary decisions in the perception of hypokinetic dysarthric speech. *Journal of the Acoustical Society of America*, *104*(4), 2457–66. doi:10.1121/1.423753

Llisterri, J. (2018). Speech analysis and transcription tools. http://liceu.uab.es/~joaquim/phonetics/fon_anal_acus/herram_anal_acus.html.

Luce, P. A., & Pisoni, D. B. (1998). Recognizing Spoken Words: The Neighborhood Activation Model. *Ear & Hearing*, *19*(1), 1–36. doi:10.1097/00003446-199802000-00001

Munro, M. J. (1998). The effects of noise on behaviour. *Studies of Second Language Acquisition*, *20*, 139–154. doi:10.1037/10037-005

Müller, K., & Wickham, H. (2018). *Tibble: Simple data frames.*

Nosek, B. A., Alter, G., Banks, G. C., Borsboom, D., Bowman, S. D., Breckler, S. J., … others. (2015). Promoting an open research culture. *Science*, *348*(6242), 1422–1425.

R Core Team. (2018). *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Rønne, F. M., Laugesen, S., & Jensen, N. S. (2017). Selection of test-setup parameters to target specific signal-to-noise regions in speech-on-speech intelligibility testing. *International Journal of Audiology*, *56*(8), 559–567. doi:10.1080/14992027.2017.1300349

Silberzahn, R., Uhlmann, E. L., Martin, D. P., Anselmi, P., Aust, F., Awtrey, E., … others. (2018). Many analysts, one data set: Making transparent how variations in analytic choices affect results. *Advances in Methods and Practices in Psychological Science*, *1*(3), 337–356.

Silge, J., & Robinson, D. (2017). *Text Mining with R*. O'Reilly Media.

Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science*, *22*(11), 1359–1366.

Tikofsky, R. S., & Tikofsky, R. P. (1964). Intelligibility Measures of Dysarthric Speech. *Journal of Speech and Hearing Research*, *7*, 325–334.

Tye-Murray, N., Sommers, M. S., & Spehar, B. (2007). Audiovisual Integration and Lipreading Abilities of Older Adults with Normal and Impaired Hearing. *Ear and Hearing*, *28*(5), 656–668. doi:10.1097/AUD.0b013e31812f7185

Van Engen, K. J., Phelps, J. E. B., Smiljanic, R., & Chandrasekaran, B. (2014). Enhancing Speech Intelligibility: Interactions Among Context, Modality, Speech Style, and Masker. *Journal of Speech Language and Hearing Research*, *57*(5), 1908. doi:10.1044/JSLHR-H-13-0076

Wicherts, J. M., Veldkamp, C. L., Augusteijn, H. E., Bakker, M., Van Aert, R., & Van Assen, M. A. (2016). Degrees of freedom in planning, running, analyzing, and reporting psychological studies: A checklist to avoid p-hacking. *Frontiers in Psychology*, *7*, 1832.

Wickham, H. (2018). *Stringr: Simple, consistent wrappers for common string operations*. Retrieved from https://CRAN.R-project.org/package=stringr

Wickham, H., François, R., Henry, L., & Müller, K. (2018). *Dplyr: A grammar of data manipulation.*

Wickham, H., & Henry, L. (2018). *Tidyr: Easily tidy data with 'spread()' and 'gather()' functions.* Retrieved from https://CRAN.R-project.org/package=tidyr

Xie, Y. (2015). *Dynamic documents with R and knitr* (2nd ed.). Boca Raton, Florida: Chapman; Hall/CRC. Retrieved from https://yihui.name/knitr/

Yorkston, K. M., & Beukelman, D. R. (1980). A clinician-judged technique for quantifying dysarthric speech based on single-word intelligibility. *Journal of Communication Disorders*, *13*(1), 15–31. doi:10.1016/0021-9924(80)90018-0