quicR: An R Library for Streamlined Data Handling of Real-Time Quaking Induced Conversion Assays

Gage R. Rowden^{a,b,c,*}, Peter A. Larsen^{a,b,c}

Abstract

Real-time quaking induced conversion (RT-QuIC) has become a valuable diagnostic tool for protein misfolding disorders such as Creutzfeldt-Jakob disease and Parkinson's disease. Given that the technology is relatively new, academic and industry standards for quality filtering data and high throughput analysis of results have yet to be fully established. The open source R library, quicR, was developed to provide a standardized approach to RT-QuIC data analysis. quicR provides functions, which can be easily integrated into existing R workflows, for data curation, analysis, and visualization.

Keywords: Chronic Wasting Disease, Creutzfeldt-Jakob Disease, Nano-QulC, RT-QulC, prion diagnostics, Parkinson's Disease, seed amplification assay

1 Metadata

Nr.	Code metadata description	Metadata
C1	Current code version	V2.1.0
C2	Permanent link to code/repository used for this code version	https://github.com/gage1145/quicR/ releases/tag/v2.1.0
C3	Permanent link to Reproducible Capsule	https://cran.r-project.org/web/packages/quicR
C4	Legal Code License	GPL-3
C5	Code versioning system used	Git
C6	Software code languages, tools, and services used	R
C7	Compilation requirements, operating environments & dependencies	R (>=4.1.0)
C8	If available Link to developer documenta- tion/manual	https://cran.r-project.org/web/ packages/quicR/quicR.pdf
_C9	Support email for questions	rowde002@umn.edu

^{*}Corresponding author.

^aDepartment of Veterinary and Biomedical Sciences, University of Minnesota, USA. ^bMinnesota Center for Prion Research and Outreach, University of Minnesota, USA. ^cPriogen Corp., USA.

¹ E-mail address: rowde002@umn.edu

1. Motivation and significance

18

19

24

25

26

27

28

30

31

32

Real-time quaking induced conversion (RT-QuIC) is within the family of seed amplification assays (SAAs), similiar to protein misfolding cyclic amplification (PMCA), and has garnered significant attention for its ultra-sensitive detection of misfolded protein aggregates [1, 2]. The assay works by converting a recombinant protein substrate into an amyloid aggregate in the presence of a misfolded seed [1, 3, 4, 5, 6, 7, 8, 9, 10]. The assay's sensitivity and specificity make RT-QuIC a promising tool for diagnosing diseases such as prion disorders and other protein misfolding pathologies [11, 12, 13, 14]. However, the relatively recent development and novelty of the assay have left a gap in widely accepted 11 academic and industry standards for data analysis and interpretation [15]. To address this gap, we introduce quicR, an open-source library, developed in R [16], dedicated to the cleaning, analysis, and visualization of RT-QuIC data. 14 By consolidating key metrics and providing robust analytical tools, quicR aims 15 to standardize the analysis pipeline and foster reproducibility within the field of 16 quaking induced assays including related assays such as Nano-QuIC [17] and 17

R workflows.
While universal diagnostic criteria for RT-QuIC have yet to be established, certain analytical metrics have emerged as valuable tools for interpreting assay results and kinetics. These include:

Micro-QuIC [18]. quicR is designed with both researchers and diagnosticians in

mind, providing a user-friendly interface that integrates seamlessly with existing

- 1. Time-to-threshold (TtT): The time required for the fluorescence signal to exceed a predefined threshold (also known as lag time) [5].
- 2. Rate of amyloid formation (RAF): A measure of the kinetics of aggregate growth, which provides insight into the relative quantity of misfolded seed [19].
- 3. Maxpoint ratio (MPR): A ratio-based metric measuring peak normalized fluorescence intensities [15].
- 4. Maximum slope (MS): The steepest rate of fluorescence increase, reflecting the most rapid phase of aggregation [20].

Together, these metrics enable researchers to characterize the kinetics of RT-QuIC reactions comprehensively, enhancing the rigor and reliability of diagnostic decisions.

In addition to analytical tools, **quicR** provides flexible and customizable visualization capabilities. Leveraging the powerful ggplot2 library [21], **quicR** enables users to generate high-quality, publication-ready figures. These visualizations can be further customized using the intuitive '+' syntax of ggplot2, allowing for tailored presentations of RT-QuIC data.

- By combining standardized metrics, advanced visualization tools, and a commit-
- ment to open source science, quicR serves as a foundational tool to empower
- researchers to analyze and present RT-QuIC data with clarity, consistency, and
- 44 cohesion.

2. Software description

6 2.1. Software architecture

- quicR was developed to address the growing need for efficient data conversion,
- analysis, and visualization of RT-QuIC data (Figure 1). The overall architecture
- revolves around integration with the proprietary MARS software (BMG Labtech,
- 50 Ortenberg, Germany) which exports raw data as Excel workbooks. The data
- from these workbooks is then curated into usable objects in the R environment,
- 52 and visualized.

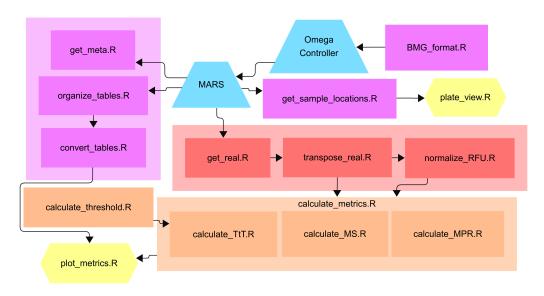


Figure 1: Workflow hierarchy of the **quicR** package. Blue nodes indicate steps where BMG software is needed. Purple nodes indicate functions dedicated to handling metadata. Red nodes are functions that acquire and manipulate raw data. Orange nodes are functions which calculate some metric. Finally, yellow nodes represent data analysis endpoints.

3 2.2. Software functionalities

The implementation of the quicR package encompasses several streamlined pro-

- cesses designed to facilitate data input, cleaning, transformation, and analysis
- of RT-QuIC data. This section provides a comprehensive guide to utilizing the
- package's key functionalities, detailing how to:

- 1. Format and input sample data into Omega control software (BMG Labtech, Ortenberg, Germany).
 - 2. Extract, clean, and organize metadata and raw data and apply transformations/normalization for downstream analysis.
 - 3. Calculate critical analytical metrics, such as time-to-threshold (TtT), rate of amyloid formation (RAF), maxpoint ratio (MPR), and maximum slope (MS).
 - 4. Visualize raw and analyzed data.

60

61

63

64

72

73

74

75

- These steps are designed to enhance reproducibility, minimize manual data handling, and enable seamless integration with the MARS software workflow.
- 8 2.2.1. Input of Sample IDs into Omega Control Software
- The Omega control software allows input of a TXT file containing sample IDs, dilution factors, and their well locations. This file is uniquely formatted, and not easily reproduced manually.
 - 1. BMG_format(): This function allows for input of a CSV file containing the plate layout (see Table 1 for proper formatting), and exports the formatted TXT file. The file can then be imported into the Omega control software before running.

	1	2	3	4	5	6	7	8	9	10	11	12
Α	Р	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11
В	Р	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11
С	Р	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11
D	Р	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11
Е	N	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11
F	N	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11
G	N	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11
Н	N	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11

Table 1: Example CSV file 96-well plate layout for input into the BMG_format() function. The top left corner is cell "A1" in the CSV file. The top numbered row and the left-most lettered column should never be altered.

6 2.2.2. Data Cleaning and Transformation

The MARS software exports real-time data as an Excel workbook. Typically, the first sheet in the workbook will include microplate views of both raw data and metadata; however, the metadata on this page is what is most useful for down-stream processes. Those tables include the "Sample IDs" and "Dilutions" tables (if dilutions were included in the MARS export). For much of the downstream analysis, it is crucial that the "Sample IDs" table was exported from MARS. If there is no table, the user can simply add it manually.

- 1. organize_tables(): returns a list of tables contained in the first sheet of the exported Excel sheet. These tables contain valuable metadata such as sample IDs, dilution factors, and microplate locations.
- 2. **convert_tables()**: accepts tables outputted from organize_tables() and converts them to columns in a data frame.
- 3. **get_sample_locations()**: extracts the well locations for each sample. Output of this function is used as an argument for visualizing a microplate-level view of real-time data.

92 2.2.3. Retrieving and Manipulating Raw Data

The raw, real-time data is typically found on the second sheet of the Excel work-book exported from MARS. There are three functions dedicated to the retrieval and cleaning of raw data.

- 1. **get_real()**: Retrieves the raw data from the Excel file, and outputs it as a data frame.
- 2. **transpose_real()**: Swaps the rows and columns which facilitates downstream analyses.
- 3. **normalize_RFU()**: normalizes the raw data by dividing each read by background fluorescence at a given cycle.

102 2.2.4. Calculations

84

85

86

89

90

96

97

98

99

100

101

109

111

112

Three analytical metrics have dedicated functions: TtT, MPR, and MS. RAF does not have a designated function since it is simply the reciprocal of the time-to-threshold (1/TtT). However, it can be calculated using the calculate_metrics() function if TtT is chosen as an optional parameter. Each function below accepts input from the transpose_real() or the normalize_RFU() functions. See Figure 2 for an example of the output of these functions.

1. calculate threhold(): returns a value which is a given number of standard deviations above the average background fluorescence of the entire microplate. This is a popular method of threshold calculation as reviewed in Rowden, et al.[15].

- 2. calculate TtT(): takes the real-time data and calculates the time in hours needed to reach a given threshold value. This threshold can be supplied by calculate threshold() or determined separately by the user.
- 3. calculate MPR(): accepts raw or normalized data and returns the maximum value obtained during the run. If supplied with raw data, it will make a call to the normalize RFU() function.
- 4. calculate _MS(): computes the approximate derivative of the real-time data and returns the maximum value obtained during the run.
- 5. **calculate_metrics()**: makes a call to functions 2–4 above and generates a data frame with the sample-matched metrics. Also computes RAF if TtT is given as an argument.

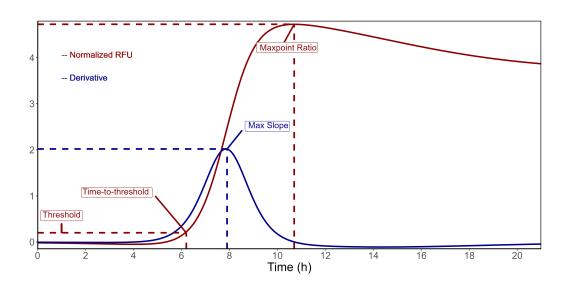


Figure 2: Example graph highlighting the calculated metrics described herein. The red curve represents a raw data curve that has been normalized against background. The maxpoint ratio is calculated as the maximum fluorescent value achieved in the normalized raw data. Time-to-threshold is determined as the time required to cross a given threshold (in this example, the threshold is set at 0.2). The blue curve represents the derivative of the raw data, and max slope is determined as the maximum of the derivative.

2.2.5. Visualization

The ensuing goal of this package is visualizing RT-QuIC data. While there are many ways to represent these data, **quicR** includes two functions which provide a rapid assessment of the RT-QuIC results.

1. plate_view(): accepts the output from the get_real() function and get sample locations() function. Makes an 8×12 or 16×24 faceted plot

- depending on if the plate has 96 or 384 wells. Each facet shows the real-time data of each well.
- 2. **plot_metrics()**: requires the output of calculate_metrics() and generates a boxplot of each sample's MPR, MS, RAF, and TtT.

2.3. Comparable Methods

1.31

To contextualize the functionality and performance of quicR, we compared it with existing RT-QulC analysis approaches from the published R package, QulC-SeedR [22], and the unpublished package, rtquicR [23]. While all three offer overlapping core functionalities, their design philosophies, input handling, and computational trade-offs differ substantially.

Benchmarking was performed using the rbenchmark library [24] with 50 replications for each function. Comparisons are approximate, as equivalent functions were not necessarily found between the three packages. Results are summarized in Table 2. In general, QulCSeedR demonstrates the fastest execution times across most core functions. However, quicR addresses several practical limitations that the authors believe justify the slower performance in some areas. Notably, QulCSeedR requires an additional, manually formatted Excel file to input sample metadata, whereas quicR directly parses both raw and meta data embedded within a single MARS export file. This design reduces user overhead and minimizes the potential for transcription errors.

The rtquicR package introduces support for additional thresholding methods and normalization strategies, and uniquely includes features such as SD50 and area-under-the-curve calculations. However, it does not currently support 384-well plate layouts, automated metadata parsing, or input files with missing data, all of which are supported by quicR. Its functions also require pre-cleaned and pre-structured input data, placing more burden on the user to prepare their dataset prior to analysis.

quicR further distinguishes itself through its modular design, allowing users to calculate metrics such as MPR, MS, TtT, and RAF independently rather than as a bundled operation. While QuICSeedR includes built-in support for bulk analysis and diagnostic outputs, these workflows can be achieved in quicR using standard R idioms (e.g., the apply family of functions), and are planned for future releases.

Overall, quicR favors flexibility, reproducibility, and usability with raw instrument output at the expense of execution speed trade-offs that align with the package's intended use in diagnostic pipelines.

Feature / Benchmark	quicR	QuICSeedR	rtquicR
Available on CRAN	Yes	Yes	No
Number of input files required	1	2	2
Number of threshold methods	2	3	4
Number of normalization methods	1	1	2
Automated metadata entry	Yes	No	No
Automated sample locations	Yes	Yes	No
Allows empty data	Yes	Yes	No
Compatible with 384-well plates	Yes	Yes	No
Built-in bulk analysis support	No	Yes	Yes
Diagnostic analysis functionality	No	Yes	No
Incorporates dilution factors	Yes	No	Yes
Converts time units	No	Yes	Yes
Calculates metrics independently	Yes	No	Yes
Calculates metrics in bulk	Yes	Yes	No
Calculates MPR	Yes	Yes	Yes
Calculates MS	Yes	Yes	No
Calculates TtT	Yes	Yes	Yes
Calculates RAF	Yes	Yes	No
Calculates area under the curve	No	No	Yes
Calculates SD50	No	No	Yes
Plate view plot execution time (s)	0.082	0.062	NA
Metric plot execution time (s)	0.009	0.005	0.007
Metric calculations (MPR, MS, etc.) (s)	0.355	0.018	NA
MPR calculation (s)	0.002	NA	0.028
TtT calculation (s)	0.001	NA	0.131
Metadata parsing time (s)	0.127	0.037	NA
Raw data parsing time (s)	0.069	0.050	0.191
Bulk analysis (s/file)	6.550	0.849	1.986

Table 2: Comparison of core features and execution times between **quicR**, QulCSeedR, and rtquicR. All benchmarks were performed using the same dataset and machine (Windows 11, 16GB RAM) in 50 replicates.

166 2.4. Reproducibility

To evaluate the reproducibility of **quicR** across systems and users, we developed oped a standardized script that processes MARS output files and writes three

key result CSV files: metadata, normalized fluorescence data, and calculated metrics as well as a plain-text file containing R session information (See Table 3). This script and accompanying raw data files were distributed, and users were instructed to source the script in the project directory. The output files were compared between each user for inconsistencies. Numerical data were given a floating point tolerance of $1E^{-12}$. Additionally, session summaries were parsed to extract R version, environment, and machine information. We did not observe any divergent results between any two users. A copy of the benchmarking script is available in the GitHub repository.

User	R Version	quicR Version	Platform	OS		
1	4.4.3	2.1.0	x86_64-w64-mingw32/x64	Windows 11 x64 (build 26100)		
2	4.4.1	2.1.0	aarch64-apple-darwin20	macOS 15.5		
3	4.4.3	2.1.0	aarch64-apple-darwin20	macOS Sequoia 15.5		
4	4.5.0	2.1.0	aarch64-apple-darwin20	macOS Sonoma 14.7.5		
5	4.4.3	2.1.0	x86_64-w64-mingw32/x64	Windows 11 x64 (build 26100)		
6	4.4.3	2.1.0	x86_64-w64-mingw32/x64	Windows 11 x64 (build 26100)		

Table 3: User session information. The script was run on both Windows and Mac machines with a variety of R versions. The quicR versions were kept identical to ensure reproducibility.

2.5. Maintenance and Community Involvement

The quicR package is developed with long-term maintainability and community engagement in mind. The source code is hosted on GitHub (https://github.com/gagerowden/quicR), where users can report issues, request features, and contribute improvements via pull requests. A comprehensive CONTRIBUTING file and issue templates are provided to streamline collaboration and to facilitate external contributions. In addition to continuous integration testing, we plan to tag releases with semantic versioning and maintain a changelog to track updates and improvements. We encourage users to share their use cases, raise issues, and help shape future development directions.

3. Illustrative examples

To demonstrate the utility of quicR, we used a typical RT-QulC run performed on a 96-well plate. The reaction was performed on a FLUOstar Omega plate reader (BMG Labtech, Ortenberg, Germany). The file was exported as an Excel workbook where the metadata appears on the first sheet and the raw data on the second sheet.

```
3.1. Example Code
194
   # Step 1: Install and load the package.
195
   install.packages("quicR")
196
   library(quicR)
197
   # Step 2:
                Identify the raw file.
   file <- "example.xlsx"
   # Step 3:
                Extract the raw data.
200
   raw <- get_real(file)[[1]]
201
   # Step 4:
                Normalize the data against the background.
202
   normal <- normalize_RFU(raw, transposed = FALSE)
203
   # Step 5:
                Extract the metadata.
204
   meta <- organize_tables(file) |> convert_tables()
205
   # Step 6: Get sample locations.
206
   locations <- get_sample_locations(file)</pre>
207
   # Step 7:
                Create the analyzed data frame.
208
   analyzed <- calculate_metrics(normal, meta)</pre>
209
   # Step 8:
                Plot the analyzed data frame.
210
   plot_metrics(analyzed)
   # Step 9: Plot the plate view.
   plate_view(raw, locations)
213
214
   Once the file name is identified, get real() is used to extract the raw data. This
215
   data is imported as a data frame with each sample designated as an individual
216
   column and the first column designated as time. Much of the downstream anal-
217
   ysis works best with background-normalized data, so the raw data is then passed
218
   to normalize RFU() [15]. This function accepts an integer as an argument for
   the desired cycle to be selected for background measurement.
220
   Next, the metadata is extracted using organize tables() and convert tables().
221
   These take the metadata found on the first sheet of the Excel file and convert
222
   them into data frame columns. Finally, metrics are calculated and assigned to
223
   their given sample ID using calculate metrics(). This generates a data frame
224
   with sample IDs, dilution factors (if chosen), MPR's, MS's, RAF's, and TtT's.
225
   Once the proper variables have been defined, they can be used as input in the
226
   visualization functions. The analyzed data frame can be used as an argument in
227
   plot metrics() to generate a plot such as Figure 3. Additionally, the raw data
228
```

4. Impact

229

Since its development in 2010 [1, 2], the utility of RT-QuIC has expanded to a host of neurodegenerative diseases caused by prions and other misfolded pro-

and sample locations are used to plot the plate view as in Figure 4.

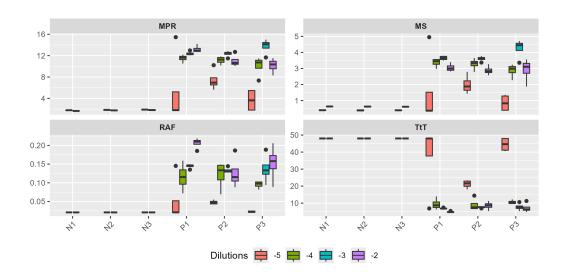


Figure 3: Boxplot of the four critical metrics calculated by the quicR package.

teins [25, 26, 27]. The improved speed and accuracy of the assay has been a boon to human health [5, 28, 29, 30] and animal management efforts [31, 32, 33, 34]. Thus, it is imperative that standardized practices and analyses are adopted. The quicR package represents a significant advancement in the standardization and reproducibility of RT-QuIC data analysis. By integrating key metrics such as TtT [5], RAF [19], MPR [15], and MS [20], quicR addresses critical gaps in the field, providing researchers and diagnosticians with a robust toolkit for interpreting RT-QuIC data.

One of the primary strengths of quicR lies in its streamlined workflow and user-centric design. The package leverages R's powerful ecosystem and the tidyverse [35] to create high-quality, customizable visualizations, ensuring accessibility for a wide range of users. Additionally, the incorporation of open-source principles allows the broader scientific community to contribute to its development, fostering innovation and adaptability.

Despite these strengths, there are limitations to consider. Currently, quicR is tailored to data exported from the MARS software, which may limit its applicability to researchers using alternative microplate readers. Future iterations of the package could expand compatibility by incorporating functions to handle diverse data formats. Furthermore, while quicR includes robust visualization tools, users seeking highly specialized plots like those made by Li, et al.[22] may require additional customization beyond the package's default capabilities.

Another avenue for improvement lies in the standardization of RT-QuIC diagnostic criteria. quicR provides tools to calculate key metrics, but consensus on

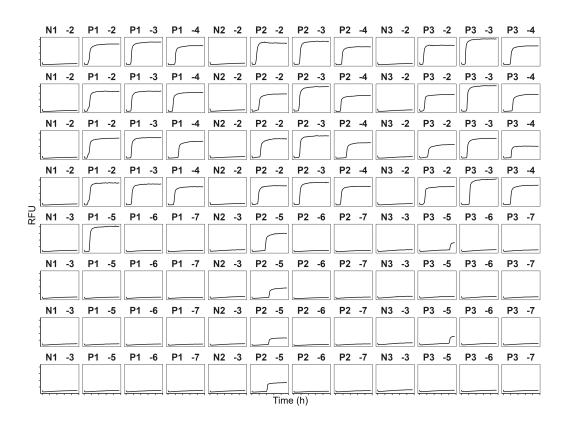


Figure 4: Plate view of RT-QuIC. Wells are identified with a sample ID and dilution factor separated by an optional delimiter (in this case, a whitespace).

thresholds and diagnostic interpretations remains a challenge for the field [15]. Collaborative efforts among researchers and clinicians are necessary to define universal criteria, enabling quicR to fully realize its potential as a diagnostic tool. Diagnostic determinations could easily be built into the library, but a larger consensus within the research community will need to be reached to warrant inclusion.

5 Conclusions

quicR offers a powerful solution for the cleaning, analysis, and visualization of RT-QulC data, addressing critical needs in a rapidly evolving field. By enabling consistent data handling and interpretation, quicR provides the foundation for improved diagnostic consistency and reproducibility. The package's open-source nature ensures that it will continue to evolve, integrating new insights and technologies as they emerge.

As RT-QuIC technology advances, tools like **quicR** will play a pivotal role in bridging the gap between assay development and practical application. By equipping researchers with reliable, standardized tools, **quicR** not only supports the study of prion and protein misfolding disorders but also serves as a model for the development of software solutions in other diagnostic fields.

274 Declaration of Conflicting Interests

Peter A. Larsen is a co-founder and stock owner, and Gage R. Rowden is a stock owner of Priogen Corp., a diagnostic company specializing in the ultra-sensitive detection of pathogenic proteins associated with prion and protein-misfolding diseases. The University of Minnesota licensed patent applications to Priogen.

279 Acknowledgements

Special thanks to Beni Altmann at The Comprehensive R Archive Network 280 (CRAN) for help during the submission process to CRAN. We thank Tiffany 281 Wolf and Marc Schwabenlander for their support through the Minnesota Cen-282 ter for Prion Research and Outreach. We thank Miranda Huang and Kristin 283 Bondo for testing the code. We would like to acknowledge Suzanne Stone and 284 Sarah Gresch for maintaining lab operations. We thank Sarah Gresch, Kendra 285 Phelps, Laramie Lindsey, Miranda Huang, and Kristin Bondo for their participation in the reproducibility study. This work was funded by the Legislative-Citizen 287 Commission on Minnesota Resources. 288

289 References

290

291

292

293

294

- [1] J. M. Wilham, C. D. Orrú, R. A. Bessen, R. Atarashi, K. Sano, B. Race, K. D. Meade-White, L. M. Taubner, A. Timmes, B. Caughey, Rapid endpoint quantitation of prion seeding activity with sensitivity comparable to bioassays, PLOS Pathog 6 (12 2010). doi:10.1371/journal.ppat. 1001217.
- [2] R. Atarashi, K. Sano, K. Satoh, N. Nishida, Real-time quaking-induced conversion: A highly sensitive assay for prion detection, Prion 5 (2011) 150-153. doi:10.4161/pri.5.3.16893.

 URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3226039/
- [3] C. D. Orrú, J. M. Wilham, L. D. Raymond, F. Kuhn, B. Schroeder, A. J. Raeber, B. Caughey, Prion disease blood test using immunoprecipitation and improved quaking-induced conversion, mBio 2 (3) (2012). doi:10. 1128/mBio.00078-11.

- [4] C. D. Orrù, B. R. Groveman, A. G. Hughson, M. Manca, L. D. Raymond, G. J. Raymond, K. J. Campbell, K. J. Anson, A. Kraus, B. Caughey, RT-QulC assays for prion disease detection and diagnostics, in: Methods in Molecular Biology, Vol. 1658, Humana Press Inc., 2017, pp. 185–203.
- [5] C. D. Orrú, B. R. Groveman, A. G. Hughson, G. Zanusso, M. B. Coulthart, B. Caughey, Rapid and sensitive rt-quic detection of human creutzfeldt-jakob disease using cerebrospinal fluid, mBio 6 (1 2015). doi:10.1128/mBio.02451-14.

 URL /pmc/articles/PMC4313917//pmc/articles/PMC4313917/
 ?report=abstracthttps://www.ncbi.nlm.nih.gov/pmc/articles/PMC4313917/
- [6] M. Bongianni, A. Ladogana, S. Capaldi, S. Klotz, S. Baiardi, A. Cagnin, D. Perra, M. Fiorini, A. Poleggi, G. Legname, T. Cattaruzza, F. Janes, M. Tabaton, B. Ghetti, S. Monaco, G. G. Kovacs, P. Parchi, M. Pocchiari, G. Zanusso, α -Synuclein RT-QulC assay in cerebrospinal fluid of patients with dementia with lewy bodies, Annals of Clinical and Translational Neurology 6 (10) (2019) 2120–2126.
- [7] R. P. Dassanayake, C. D. Orrú, A. G. Hughson, B. Caughey, T. Graça, D. Zhuang, S. A. Madsen-Bouterse, D. P. Knowles, D. A. Schneider, Sensitive and specific detection of classical scrapie prions in the brains of goats by real-time quaking-induced conversion, J. Gen. Virol. 97 (3) (2016) 803–812.
- [8] S. Hwang, M. H. West Greenlee, A. Balkema-Buschmann, M. H. Groschup, E. M. Nicholson, J. J. Greenlee, Real-time quaking-induced conversion detection of bovine spongiform encephalopathy prions in a subclinical steer, Frontiers in Veterinary Science 4 (JAN) (2018) 19.
- [9] B. R. Groveman, C. D. Orrù, A. G. Hughson, L. D. Raymond, G. Zanusso, B. Ghetti, K. J. Campbell, J. Safar, D. Galasko, B. Caughey, Rapid and ultra-sensitive quantitation of disease-associated α -synuclein seeds in brain and cerebrospinal fluid by α Syn RT-QuIC, Acta Neuropathologica Communications 6 (1) (2018) 7.
- [10] M. A. Metrick, 2nd, N. d. C. Ferreira, E. Saijo, A. Kraus, K. Newell, G. Zanusso, M. Vendruscolo, B. Ghetti, B. Caughey, A single ultrasensitive assay for detection and discrimination of tau aggregates of alzheimer and pick diseases, Acta Neuropathol Commun 8 (1) (2020) 22.
- ³³⁷ [11] M. Fiorini, G. Iselle, D. Perra, M. Bongianni, S. Capaldi, L. Sacchetto, S. Ferrari, A. Mombello, S. Vascellari, S. Testi, S. Monaco, G. Zanusso, High

- diagnostic accuracy of rt-quic assay in a prospective study of patients with suspected scjd, International Journal of Molecular Sciences 21 (3) (2020). doi:10.3390/ijms21030880.

 URL https://www.mdpi.com/1422-0067/21/3/880
- M. Rossi, S. Capellari, A. G. Hughson, N. McKenzie, F. Moda, M. Rossi, S. Capellari, A. Green, G. Giaccone, B. Caughey, P. Parchi, High diagnostic value of second generation csf rt-quic across the wide spectrum of cjd prions, Sci Rep (9 2017). doi:10.1038/s41598-017-10922-w.
- [13] C. Picasso-Risso, M. D. Schwabenlander, G. Rowden, M. Carstensen, J. C. Bartz, P. A. Larsen, T. M. Wolf, Assessment of Real-Time Quaking-Induced conversion (RT-QuIC) assay, immunohistochemistry and ELISA for detection of chronic wasting disease under field conditions in White-Tailed deer:

 A bayesian approach, Pathogens 11 (5) (2022).
- [14] C. L. Holz, J. R. Darish, K. Straka, N. Grosjean, S. Bolin, M. Kiupel, S. Sreevatsan, Evaluation of Real-Time Quaking-Induced conversion, ELISA, and immunohistochemistry for chronic wasting disease diagnosis, Front Vet Sci 8 (2021) 824815.
- [15] G. R. Rowden, C. Picasso-Risso, M. Li, M. D. Schwabenlander, T. M. Wolf, P. A. Larsen, Standardization of data analysis for rt-quic-based detection of chronic wasting disease, Pathogens 12 (2023) 309. doi: 10.3390/PATHOGENS12020309/S1. URL https://www.mdpi.com/2076-0817/12/2/309/htmhttps://www.mdpi.com/2076-0817/12/2/309
- [16] R Core Team, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria (2024).

 URL https://www.R-project.org/
- [17] P. R. Christenson, M. Li, G. Rowden, P. A. Larsen, S.-H. Oh, Nanoparticle-enhanced rt-quic (nano-quic) diagnostic assay for misfolded proteins, Nano Letters 23 (9) (2023) 4074-4081, pMID: 37126029. arXiv:https://doi.org/10.1021/acs.nanolett.3c01001, doi:10.1021/acs.nanolett.3c01001.

 URL https://doi.org/10.1021/acs.nanolett.3c01001
- 171 [18] D. J. Lee, P. R. Christenson, G. Rowden, N. C. Lindquist, P. A. Larsen, S.-H. Oh, Rapid on-site amplification and visual detection of misfolded proteins via microfluidic quaking-induced conversion (micro-quic), npj Biosensing 1 (6) (7 2024). doi:10.1038/s44328-024-00006-x.

- URL https://www.nature.com/articles/s44328-024-00006-x#citeas
- N. J. Gallups, A. S. Harms, 'seeding' the idea of early diagnostics in synucleinopathies, Brain 145 (2022) 418–419. doi:10.1093/BRAIN/AWAC062. URL https://dx.doi.org/10.1093/brain/awac062
- ³⁸⁰ [20] D. M. Henderson, K. A. Davenport, N. J. Haley, N. D. Denkers, C. K. Mathiason, E. A. Hoover, Quantitative assessment of prion infectivity in tissues and body fluids by real-time quaking-induced conversion, Journal of General Virology 96 (2015) 210–219. doi:10.1099/vir.0.069906-0.
- [21] H. Wickham, ggplot2: Elegant Graphics for Data Analysis, Springer-Verlag
 New York, 2016.
 URL https://ggplot2.tidyverse.org
- ³⁸⁷ [22] M. Li, D. N. Bryant, S. Gresch, M. S. Milstein, P. R. Christenson, S. S. Lichtenberg, P. A. Larsen, S. H. Oh, QulCSeedR: An R package for analyzing fluorophore-assisted seed amplification assay data, Bioinformatics 41 (1) (2025) 1–7. doi:10.1093/bioinformatics/btae752.
- [23] J. Slota, rtquicr, https://github.com/jslota/rtquicR (2023).
- W. Kusnierczyk, rbenchmark: Benchmarking routine for R, r package version 1.0.0 (2012).

 URL https://CRAN.R-project.org/package=rbenchmark
- [25] C. D. Orrú, B. R. Groveman, A. G. Hughson, T. Barrio, K. Isiofia, B. Race,
 N. C. Ferreira, P. Gambetti, D. A. Schneider, K. Masujin, K. Miyazawa,
 B. Ghetti, G. Zanusso, B. Caughey, Sensitive detection of pathological seeds
 of α-synuclein, tau and prion protein on solid surfaces, PLOS Pathogens
 20 (4) (2024) 1–22. doi:10.1371/journal.ppat.1012175.
 URL https://doi.org/10.1371/journal.ppat.1012175
- $_{401}$ [26] E. Alwakil, Chapter 6 α -synuclein seeding assay and analysis, in: W. Mohamed (Ed.), Translational Models of Parkinson's Disease and Related Movement Disorders, Academic Press, 2025, pp. 97–109. doi:https://doi.org/10.1016/B978-0-443-16128-5.00006-2. URL https://www.sciencedirect.com/science/article/pii/B9780443161285000062
- 407 [27] Z. Wang, L. Wu, M. Gerasimenko, T. Gilliland, S. A. Gunzler, V. Donadio, R. Liguori, B. Xu, W.-Q. Zou, R. Article, Seeding Activity of Skin Misfolded Tau as a Biomarker for Tauopathies, Molecular Neurodegeneration (2024)

- 1-19doi:10.1186/s13024-024-00781-1. URL https://doi.org/10.21203/rs.3.rs-3968879/v1
- [28] A. J. Green, Rt-quic: a new test for sporadic cjd, Practical neurology 19 (1) (2019) 49–55.
- B. Race, K. Williams, B. Chesebro, Transmission studies of chronic wasting disease to transgenic mice overexpressing human prion protein using the rt-quic assay, Veterinary research 50 (1) (2019) 6.
- [30] S. Vascellari, C. D. Orrù, B. Caughey, Real-time quaking-induced conversion assays for prion diseases, synucleinopathies, and tauopathies, Frontiers in Aging Neuroscience 14 (2022) 853050.
- [31] M. H. Huang, S. Demarais, M. D. Schwabenlander, B. K. Strickland, K. C.
 VerCauteren, W. T. McKinley, G. Rowden, C. C. Valencia Tibbitts, S. C.
 Gresch, S. S. Lichtenberg, et al., Chronic wasting disease prions on deer
 feeders and wildlife visitation to deer feeding areas, The Journal of Wildlife
 Management (2025) e70000.
- [32] S. K. Cooper, C. E. Hoover, D. M. Henderson, N. J. Haley, C. K. Mathiason, E. A. Hoover, Detection of cwd in cervids by rt-quic assay of third eyelids, PloS one 14 (8) (2019) e0221654.
- [33] R. B. Piel III, S. E. Veneziano, E. M. Nicholson, D. P. Walsh, A. D. Lomax, T. A. Nichols, C. M. Seabury, D. A. Schneider, Validation of a real-time quaking-induced conversion (rt-quic) assay protocol to detect chronic wasting disease using rectal mucosa of naturally infected, pre-clinical white-tailed deer (odocoileus virginianus), PLoS One 19 (6) (2024) e0303037.
- 433 [34] E. Harpaz, F. A. Cazzaniga, L. Tran, T. T. Vuong, G. Bufano, Ø. Salvesen,
 434 M. Gravdal, D. Aldaz, J. Sun, S. Kim, et al., Transmission of norwegian
 435 reindeer cwd to sheep by intracerebral inoculation results in an unusual
 436 phenotype and prion distribution, Veterinary Research 55 (1) (2024) 94.
- [35] H. Wickham, M. Averick, J. Bryan, W. Chang, L. D. McGowan, R. François,
 G. Grolemund, A. Hayes, L. Henry, J. Hester, M. Kuhn, T. L. Pedersen,
 E. Miller, S. M. Bache, K. Müller, J. Ooms, D. Robinson, D. P. Seidel,
 V. Spinu, K. Takahashi, D. Vaughan, C. Wilke, K. Woo, H. Yutani, Welcome
 to the tidyverse, Journal of Open Source Software 4 (43) (2019) 1686.
 doi:10.21105/joss.01686.