A Robustness Reproduction of “Do We Become More Lonely With Age? A Coordinated Data Analysis of Nine Longitudinal Studies”

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Abstract

The original study by Graham et al. (2024) investigated whether loneliness changes with age across the adult lifespan, synthesizing data from nine longitudinal studies via meta-analyses. The primary finding was that loneliness follows a U-shaped trajectory: decreasing from young adulthood to midlife and increasing in older adulthood (estimated Age^2 regression coefficient of 0.07 with 95% confidence interval from 0.02 to 0.13, age centered at 60 years). We computationally reproduced the reported meta-analyses. We assessed the robustness of the main finding with respect to alternative analytic decisions regarding the estimation of the heterogeneity variance and inclusion/exclusion of individual studies. We find that the main claim from Graham et al. (2024) is robust regarding these decisions.

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The authors have no relation to Graham et al. and declare no conflict of interest.
Code and data to reproduce our analyses are available at https://github.com/SamCH93/loneliness-trajectories.
We thank Abel Brodeur from the Institute for Replication for support and advice.
This robustness reproduction was carried out in parts at the “Replication Games” workshop at the META-REP 2024 conference (October 28-31 2024, Munich, Germany). The authors compiled a pre-analysis plan before attending the workshop. The plan was not formally preregistered but sent to Abel Brodeur on October 27 by email, and is also available on our code repository.

1. Introduction

Graham et al. (2024) conducted a coordinated data analysis of nine longitudinal data sets in order to assess whether loneliness changes across the adult lifespan. Here we assess the computational reproducibility and the robustness of the main claim of the original paper (from the abstract):

"Analyses revealed that loneliness follows a U-shaped curve, decreasing from young adulthood to midlife and increasing in older adulthood."

which was based on an estimated Age^2 regression coefficient of 0.07 with 95% confidence interval (CI) from 0.02 to 0.13, obtained from random-effects meta-analysis of the adjusted Age^2 regression coefficient from the individual data sets.

We first investigate whether we can computationally reproduce this claim (Section 2) using the code and data provided by the original authors. In Section 3 we then assess the main claims' robustness regarding the following analytic decision: i) Choosing different methods to estimate the between data set heterogeneity variance (DerSimonian Laird, Paule-Mandel, Empirical Bayes) in addition to the originally used Restricted maximum likelihood (REML) method, ii) applying a leave-one-out robustness check to see whether the conclusion remains the same when each study is excluded or whether a single study drives the results. We report our final conclusions in Section 4.

2. Computational Reproducibility

The GitHub repository (https://github.com/emoriebeck/loneliness-trajectories) mentioned in the original paper contains the complete cleaning code, the analysis code, and the analysis data. The raw data from the nine longitudinal studies was not available and would require obtaining them from the individual study websites. For the computational reproduction check we therefore used the code and analysis data from the aforementioned repository and focused on reproducing the meta-analyses (file: `02-scripts/03-meta-analysis.Rmd`) .

In the initial attempt the meta-analyses were not computationally reproducible: We cloned the GitHub repository and began to run the script. We encountered some minor issues due to the fact that the script includes absolute paths and does not load necessary packages. Moreover, the script is contingent upon the cleaning script (file `02-scripts/01-data-cleaning.Rmd`) due to some variables being reused (e.g., `studies` or `wd`). Consequently, we had to search for the needed code in the other scripts and rerun it. Additionally, the repository lacks a README file, which could provide essential context and guidance.

The primary obstacle to computational reproducibility was our initial inability to load the requisite .RData files for conducting the meta-analysis. For example, when initially loading the file `imp_OCTOTWIN_Quadratic_slope_AllInteraction_adj.RData` (from the folder `03-results/01-models/)`, the following error message was obtained

```
bad restore file magic number (file may be corrupted) -- no data loaded

In addition: Warning message:

file ‘imp_OCTOTWIN_Quadratic_slope_AllInteraction_adj.RData’ has magic
number 'versi'

  Use of save versions prior to 2 is deprecated
```

We reproduced the same error on two Windows, one Mac, and one Linux system. We then attempted to download the entire repository as a zip file and from OSF (https://osf.io/67tfa/) instead of downloading via `git clone`, yet the same issue persisted. However, downloading a single .RData file manually proved successful, as the file was accessible and did not produce any errors upon loading. Since a full download of the repository would require a manual download of at least 150 individual models, we reached out to the authors via the Institute for Replication. The authors confirmed that they also encountered this issue when downloading files from OSF but not via Git, and offered a workaround script to download the files via the GitHub API. However, after further investigations, we discovered that the issue was caused by GitHub's Git Large File Storage (Git LFS) system that was enabled for the authors' GitHub repository as it included many large files. Installing Git LFS and running

```
git lfs pull
```

within the cloned repository downloaded the necessary files (about 20GB of data). When re-cloning the Git repository, the large files were again included, which explains why the authors could not reproduce our issue as they had already pre-saved the large files on their computers. However, the necessity of using Git LFS was not clearly documented and could have been explicitly stated in a README file, as enabling Git LFS is essential for a complete and accurate repository download.[1] Furthermore, the authors have linked the GitHub repository to an OSF repository where Git LFS is not supported, so the files downloaded from OSF are unfortunately inaccessible.

[1] Most comprehensive Git installations (version 2.14.1 and later) include Git LFS by default. Explicitly specifying the requirement for Git LFS ensures that users with standard Git configurations can correctly retrieve such large files, as many installations do not enable LFS by default. Without this clarification, users may inadvertently download only pointer files instead of the actual data, resulting in incomplete or failed reproduction attempts, as was the case with our first attempts in retrieving the repository.

After overcoming this issues, we were able to rerun the meta-analysis script on both a Windows and Linux system, reproducing all figures, including `age2-imp-Quadratic-slope-Main-adj.png` (directory `03-results/09-plots/02-forest-plots/png/`) and `imp-Quadratic-slope-adj.png` (directory `03-results/09-plots/01-trajectories/main/`), which represent the key Figures 1a and 1b from the paper, see Figure 1 in the Appendix.

In sum, our computational reproduction was successful. However, to improve computational reproducibility we recommend clearer instructions on:

1. Repository setup guidance via centralized documentation – provide clearer instructions on how to properly clone and initialize the reproduction environment. Consolidating this information in a README-file to make the reproduction process more accessible and transparent, ensures a smooth reproduction process.
2. Dependency management – Listing required packages along with version details (e.g., via a `sessionInfo()` output or a lock file) to ensure compatibility across computational environments.
3. File dependencies and execution order – Clarifying which scripts or files need to be modified or rerun to reproduce the key analyses and figures.

3. Discrepancies Between Pre-analysis Plan and Article

The original study was preregistered and included a pre-analysis plan (https://osf.io/89t5d). Any discrepancies between the preregistered plan and the actual study are outlined by the authors and justified in an accompanying document within the OSF repository (https://osf.io/w3rv5). The hypotheses and statements regarding the sample referenced in the preregistration align with the information presented in the paper, and any discrepancies are duly explained in the supplementary document. Further, the statistical procedures are described in the preregistration which we did not retrace due to the length of the script.

4. Robustness Reproduction

We loaded the fitted model objects based on the quadratic age term adjusted for other variables and based on the imputed data sets. We then extracted the Age^2 regression coefficients and their standard errors, and manually applied Rubin's rule to pool the point estimates and standard errors from the five imputed datasets (see e.g., Section 2.3.2 in van Buuren, 2021). The resulting forest plot aligned with the one reported in the original paper, see Figure 2 and Table 2 in the Appendix.

We then performed two types of robustness checks on the meta-analysis model. First, refitting the meta-analysis model with Paule-Mandel, empirical Bayes, or DerSimonian-Laird variance estimation produced point estimates that were very similar to the original REML-based estimate (see e.g., Veroniki, 2016, for an overview of heterogeneity estimators). Similarly, the 95% confidence intervals all exclude the null value of zero, and thus the qualitative conclusions are robust to the chosen estimation approach. These results are summarized in Figure 3 and Table 2 in the Appendix.

Second, a leave-one-out check was applied (Viechtbauer, 2021). That is, we re-ran the meta-analysis (with REML estimation) excluding each dataset individually and assessing the resulting meta-analytic point estimate and confidence interval. This led to some variation in the point estimates. However, the qualitative conclusion remained robust as all 95% CIs still excluded the null value, see Figure 3 and Table 2 in the Appendix.

5. Conclusion

In conclusion, our robustness reproduction of Graham et al. (2024) showed that their meta-analyses could be reproduced based on the analysis data provided, although there were some undocumented computational obstacles in obtaining all data files due to their large size. Moreover, we showed that their main claim of a quadratic age effect is robust against plausible alternative choices regarding estimation of the heterogeneity variance and study exclusion/inclusion. The analytic code for our analyses is available at https://github.com/SamCH93/loneliness-trajectories.

References

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Tables

Table 1: Replication Package Contents and Reproducibility

	Fully	**Partial**	**No**
Raw data provided			x
Cleaning code provided	x		
Analysis data provided	x		
Analysis code provided	x		
Reproducible from raw data			x
Reproducible from analysis data	x		

Table 2: Numerical robustness check results

Robustness check	Lower 95%CI	Point estimate	Upper 95%CI	SE	*P*-value (two-sided)
REML estimation (original)	0.017	0.072	0.127	0.028	0.011
DL estimation	0.025	0.070	0.115	0.023	0.002
PM estimation	0.012	0.073	0.133	0.031	0.018
EB estimation	0.012	0.073	0.133	0.031	0.019
HILDA exclusion	0.038	0.089	0.140	0.026	0.001
LISS exclusion	0.024	0.084	0.144	0.031	0.006
GSOEP exclusion	0.016	0.080	0.143	0.032	0.014
HRS exclusion	0.007	0.072	0.137	0.033	0.030
SATSA exclusion	0.003	0.064	0.126	0.031	0.041
ELSA exclusion	0.002	0.061	0.120	0.030	0.044
SHARE exclusion	0.002	0.057	0.113	0.028	0.043
OCTOTWIN exclusion	0.014	0.069	0.124	0.028	0.014

Figures

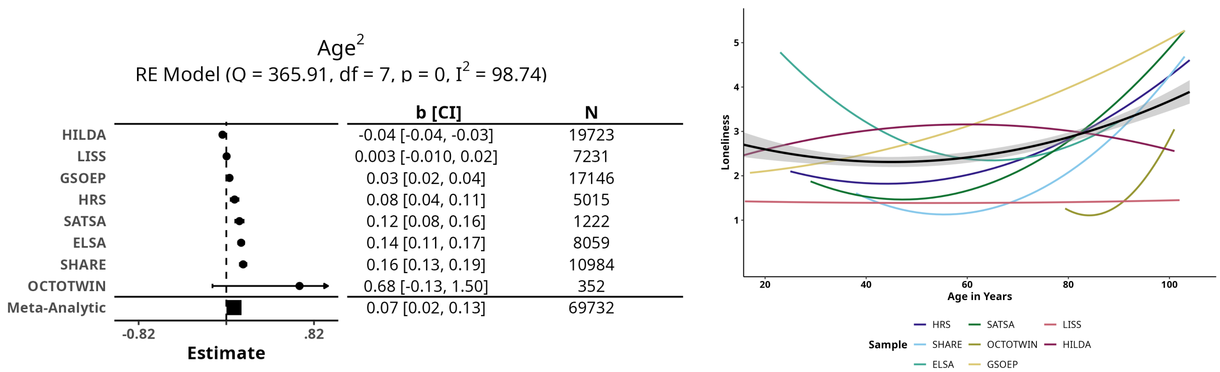

Figure 1: Reproduced Figures 1a (left) and 1b (right)

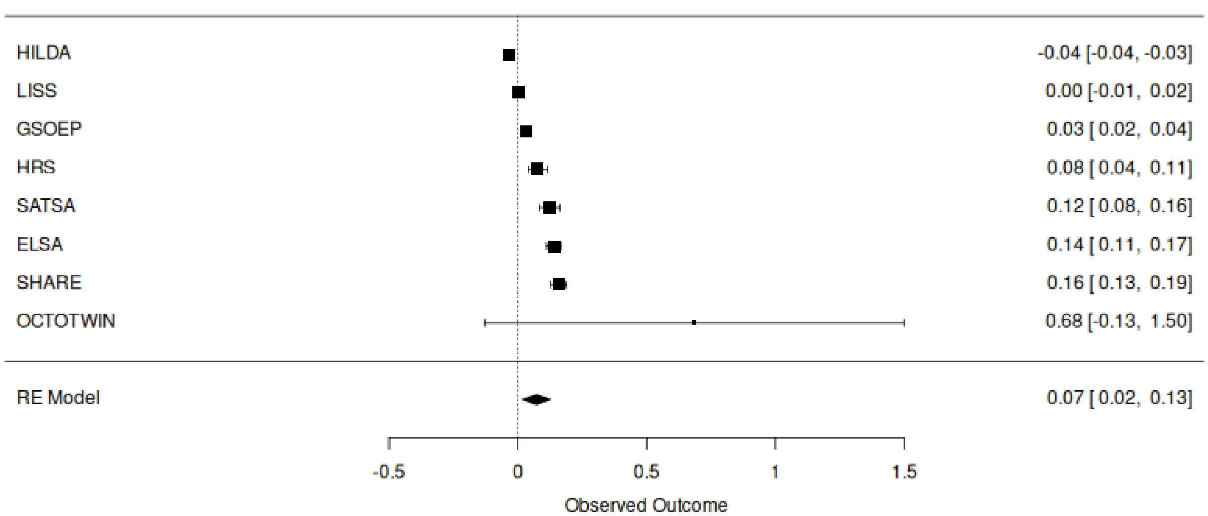

Figure 2: Re-created forest plot

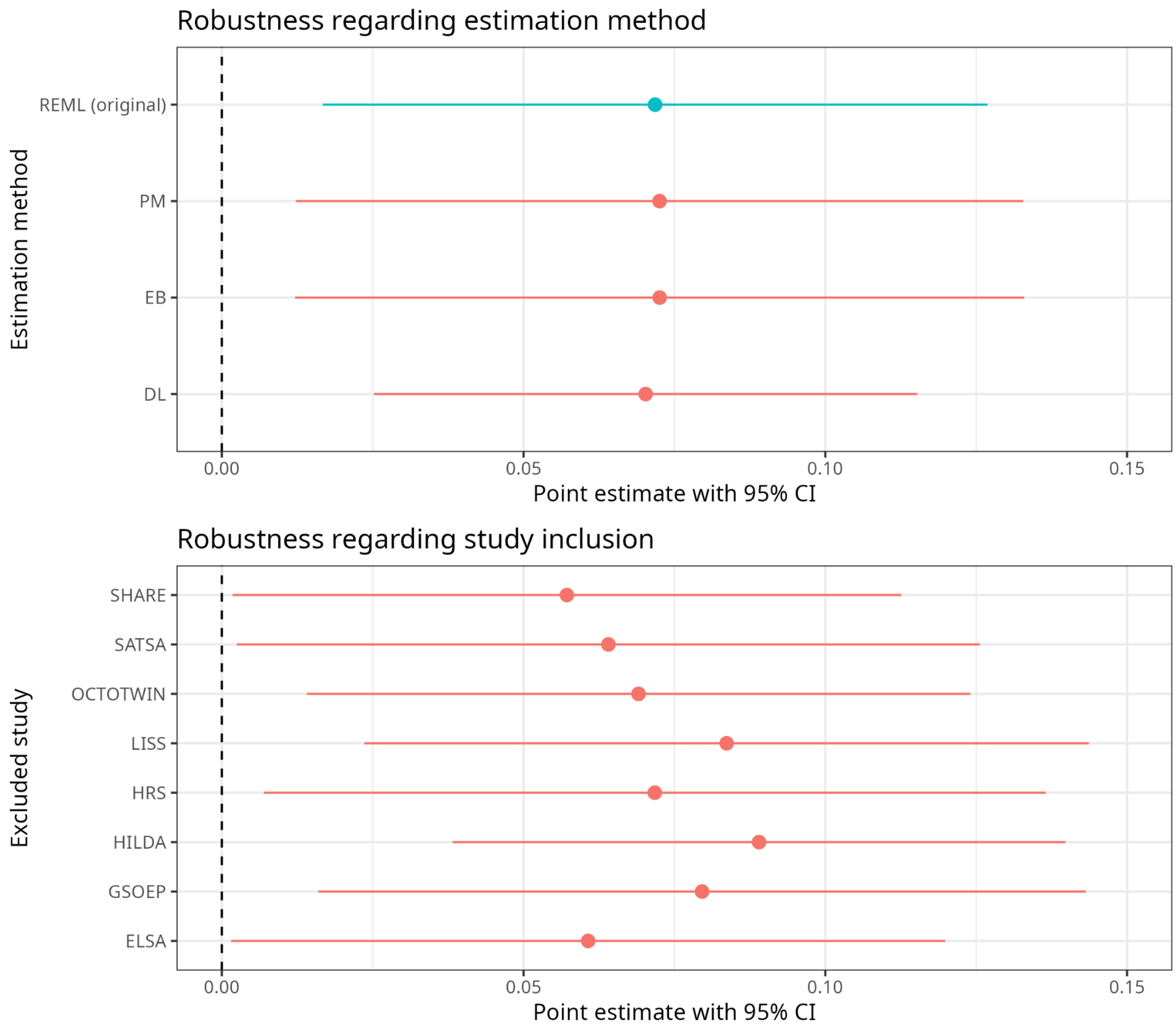

Figure 3: Visual robustness check results