Journal of the International Neuropsychological Society (2024), 1–6
doi:10.1017/S1355617724000031

Brief Communication

Facilitating clinical use of the Amsterdam Instrumental Activities of Daily Living Questionnaire: Normative data and a diagnostic cutoff value

Merel C. Postema[1,2], Mark A. Dubbelman[1,2,3,4], Jürgen Claesen[5], Craig Ritchie[6], Merike Verrijp[7], Leonie Visser[1,2], Pieter-Jelle Visser[1,2,8], Marissa D. Zwan[1,2], Wiesje M. van der Flier[1,2] and Sietske A.M. Sikkes[1,2,9]

[1]Alzheimer Center Amsterdam, Neurology, Vrije Universiteit Amsterdam, Amsterdam UMC location VUmc, Amsterdam, Amsterdam, The Netherlands, [2]Amsterdam Neuroscience, Neurodegeneration, Amsterdam, The Netherlands, [3]Department of Neurology, Massachusetts General Hospital, Harvard Medical School, Boston, MA, USA, [4]Department of Neurology, Brigham and Women's Hospital, Center for Alzheimer Research and Treatment, Harvard Medical School, Boston, MA, USA, [5]Department of Epidemiology and Data Science, Amsterdam University Medical Centers, Amsterdam, Netherlands, [6]Centre for Clinical Brain Sciences, The University of Edinburgh, Edinburgh, UK, [7]Brain Research Center, Amsterdam, The Netherlands, [8]Department of Psychiatry and Neuropsychology, School for Mental Health and Neuroscience (MHeNS), Maastricht University, Maastricht, The Netherlands and [9]Faculty of Behavioural and Movement Sciences, Clinical, Neuro and Developmental Psychology, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

Abstract

Objective: The Amsterdam Instrumental Activities of Daily Living Questionnaire (A-IADL-Q) is well validated and commonly used to assess difficulties in everyday functioning regarding dementia. To facilitate interpretation and clinical implementation across different European countries, we aim to provide normative data and a diagnostic cutoff for dementia. **Methods:** Cross-sectional data from Dutch Brain Research Registry (N = 1,064; mean (M) age = 62 ± 11 year; 69.5% female), European Medial Information Framework-Alzheimer's Disease 90 + (N = 63; Mage = 92 ± 2 year; 52.4% female), and European Prevention of Alzheimer's Dementia Longitudinal Cohort Study (N = 247; Mage = 63 ± 7 year; 72.1% female) were used. The generalized additive models for location, scale, and shape framework were used to obtain normative values (Z-scores). The beta distribution was applied, and combinations of age, sex, and educational attainment were modeled. The optimal cutoff for dementia was calculated using area under receiver operating curves (AUC-ROC) and Youden Index, using data from Amsterdam Dementia Cohort (N = 2,511, Mage = 64 ± 8 year, 44.4% female). **Results:** The best normative model accounted for a cubic-like decrease of IADL performance with age that was more pronounced in low compared to medium/high educational attainment. The cutoff for dementia was 1.85 standard deviation below the population mean (AUC = 0.97; 95% CI [0.97–0.98]). **Conclusion:** We provide regression-based norms for A-IADL-Q and a diagnostic cutoff for dementia, which help improve clinical assessment of IADL performance across European countries.

Keywords: A-IADL-Q; everyday functioning; dementia; norm scores; clinical implementation; results interpretation

(Received 4 July 2023; final revision 21 November 2023; accepted 2 January 2024)

Introduction

Difficulties in performing cognitively complex everyday activities, so-called "instrumental activities of daily living" (IADL), are a diagnostic criterion for dementia. One way to measure IADL functioning is by means of the Amsterdam Instrumental Activities of Daily Living Questionnaire (A-IADL-Q), an extensively validated study partner-reported instrument (see e.g. [Dubbelman et al., 2020; Jutten et al., 2017; Koster et al., 2015; Sikkes et al., 2013; Sikkes et al., 2013]). To interpret A-IADL-Q scores on an individual level and to successfully implement IADL in clinical practice, normative data are imperative.

Norm scores typically reflect the standardized difference between an individual's observed and expected outcome measure, as based on a cognitively healthy reference population. Hence they are imperative for results interpretation, which is particularly useful in clinical practice. Nevertheless, researchers can also benefit from the availability of norm scores, as they allow additional research opportunities, like splitting clinical cohorts based on individual deviations from normal functioning, which encourages personalized treatments (Marquand et al., 2016). Clinical use of the A-IADL-Q can be further facilitated by a norm-based diagnostic cutoff value, which aids in the diagnostic process and subsequent communication of results.

Traditional norming has the important limitation that it treats all demographic variables as discrete values (Voncken et al., 2019).

Corresponding authors: Merel C. Postema; Email: m.c.postema@amsterdamumc.nl, Sietske A.M. Sikkes; Email: s.sikkes@amsterdamumc.nl

Cite this article: Postema M.C., Dubbelman M.A., Claesen J., Ritchie C., Verrijp M., Visser L., Visser P.-J., Zwan M.D., van der Flier W.M., & Sikkes S.A.M. Facilitating clinical use of the Amsterdam Instrumental Activities of Daily Living Questionnaire: Normative data and a diagnostic cutoff value. *Journal of the International Neuropsychological Society*, 1–6, https://doi.org/10.1017/S1355617724000031

As a result, this approach has been widely replaced by continuous norming, including standard polynomial regression and generalized additive models for location, scale, and shape (GAMLSS). The first allows for varying means, while the latter additionally allows for varying scale (σ, approximate coefficient of variation), skewness (ν, transformation to symmetry), and kurtosis (τ, power exponential parameter) (Voncken et al., 2019). Due to this flexibility, and because it is efficient, regression-based norming using GAMLSS has become a highly popular approach to estimate norm scores for psychological tests (Timmerman et al., 2021).

Here, we aimed to establish demographically adjusted norm scores for the A-IADL-Q using GAMLSS. Several combinations of age, sex and/or education were fitted to find the best normative model. Additionally, we aimed to provide the optimal cutoff value to distinguish cognitively normal (CN) from dementia, along with its diagnostic accuracies for other diagnostic contrasts, including subjective cognitive decline (SCD) and mild cognitive impairment (MCI) diagnoses.

Methods

Ethical considerations and consent

This study made use of European data from multiple studies, all of which were approved by ethical review boards local to each study site. All participants provided written informed consent to store, share, and use their data for research purposes. The research was completed in accordance with Helsinki Declaration.

Participant selection criteria

See Supplementary Methods for information. Figure S1 shows a flowchart of our exclusion criteria.

Sample characteristics

Cognitively normal sample

Cross-sectional data from Dutch Brain Research Registry (Zwan et al., 2021), European Medical Information Framework – Alzheimer's Disease (EMIF-AD) 90 + study (Legdeur et al., 2018), and European Prevention of Alzheimer's Dementia Longitudinal Cohort Study (EPAD-LCS) (Ritchie et al., 2016) were combined into one large, European normative sample of 1,374 participants with a wide age range (mean age = 63.3 ± 11.9 years [min = 18, max = 97years], 69.2% female, 69.8% highly educated). See Supplementary Methods for details per dataset.

Memory clinic sample

In order to compute the optimal cutoff value to distinguish normal functioning from dementia, the CN sample was combined with a memory clinic sample from the Amsterdam Dementia Cohort (ADC) (van der Flier & Scheltens, 2018), comprising 2,155 individuals recruited from the Alzheimer Center Amsterdam between 2013 and 2022 (mean age = 64 ± 8years [min = 32, max = 86 years], 44.4% female, 42.0% highly educated).

Measures

A-IADL-Q

The A-IADL-Q is a well-validated, study partner-reported questionnaire, measuring impairments in everyday functioning in the context of dementia (Dubbelman et al., 2020; Jutten et al., 2017; Koster et al., 2015; Sikkes et al., 2013; Sikkes et al., 2013). The shortened version counts 30 items, each of which is scored according to a 5-point Likert scale (ranging from no difficulty to unable to perform a certain task). Total scores were calculated using item response theory (IRT), resulting in T-scores that are normally distributed in a memory clinic population around a mean of 50 with a standard deviation of 10, where higher scores indicate better IADL functioning (Jutten et al., 2017). For the purpose of fitting a GAMLSS with a beta distribution, the T-scores were divided by 100, such that the values fell within the beta interval [0,1].

Other measures

Education of participants was either measured in years or classified according to the Dutch 'Verhage' system, and dichotomized to low/medium (i.e., < 13 years of education, or Verhage scales 1–5; up to high school education) and high education (i.e., ≥13 years of education, or Verhage scales 6-7; college level degree).

Statistical analyses

All analyses were performed in R version 4.2.1. The R packages gamlss (Rigby & Stasinopoulos, 2005) and cutpointr (Thiele & Hirschfeld, 2021) were used for fitting GAMLSS and establishing the optimal diagnostic cutoff value, respectively.

The normative model

To determine the appropriate distribution family for our normative sample, a histogram plot of the A-IADL-Q T-scores was visually inspected. The beta distribution was found appropriate (see results), and accordingly used for fitting GAMLSS with various combinations of age (years), sex (0 = male, 1 = female) and educational attainment (0 = low, 1 = medium/high), including interaction effects and a cubic smoothing spline function for age. Stepwise model selection using a Generalized Akaike Information Criterion (GAIC) was used to determine the optimal model, i.e. the model with the lowest GAIC value. A Worm plot (i.e., de-trended Q-Q plot) of the optimal model was visually inspected to determine model fit, and term plots were created to display the cubic smoothing spline functions that were fitted.

Generalizability of the normative model was tested using k-folds cross validation, and norm scores (i.e., Z-scores, or normalized quantile residuals) were obtained for each individual in the joint study sample (see Supplementary Methods for details).

The optimal diagnostic cutoff value and corresponding diagnostic accuracies

The optimal cutoff value to distinguish CN individuals from those with dementia was derived from a bootstrap average estimate on the Youden Index, i.e., a metric of accuracy, whereby the highest value represents the optimal balance between sensitivity and specificity. Bootstraps were run with 500 repeats, to optimize this metric. The diagnostic accuracy was determined by means of Area Under Received Operating Curves (AUC-ROC).

The diagnostic accuracy of the optimal cutoff value for (1) CN vs dementia (CNvsDem) was also calculated for other diagnostic groups: (2) CN vs MCI (CNvsMCI), (3) SCD vs MCI (SCDvsMCI), (4) SCD vs dementia (SCDvsDem), and (5) MCI vs dementia (MCIvsDem).

Results

Sample characteristics

Our CN sample comprised 1,374 individuals, and the memory clinic sample comprised 1,725 individuals. Table 1 displays

https://doi.org/10.1017/S1355617724000031 Published online by Cambridge University Press

Table 1. Participant characteristics

	Total ($N = 3,529$)					
		Cognitively normal sample ($N = 1,374$)				Memory clinic sample ($N = 2,155$)
		Dutch Brain Research Registry	EMIF-AD 90+	EPAD-LCS	Total	ADC
Age						
Mean (*SD*)	63.3 (11.9)	61.8 (11.0)	92.1 (1.9)	62.5 (6.8)	63.3 (11.9)	64.2 (8.1)
Median (Range)	64 (18–97)	63 (18– 93)	91.8 (88–97)	62 (50–85)	63 (18–97)	65 (32–86)
Female, *N* (%)	951 (69.2%)	740 (69.5%)	33 (52.4%)	178 (72.1%)	951 (69.2%)	930 (43.2%)
High education, *N* (%)	959 (69.8%)	737 (69.3%)	27 (42.9%)	195 (78.9%)	959 (69.8%)	919 (42.6%)
A-IADL-Q score						
Mean (*SD*)	66.5 (4.7)	66.5 (4.2)	57.3 (8.5)	68.8 (1.5)	66.5 (4.7)	51.6 (10.1)
Range	36.5–70.0	47.5–70.0	36.5–70.0	58.9–70.0	36.5–70.0	18.5–70.0
Diagnosis, *N* (%)						
CN	1374 (39%)	1,064 (100%)	63 (100%)	247 (100%)	1374 (100%)	–
SCD	592 (17%)	–	–	–	–	592 (27%)
MCI	319 (9%)	–	–	–	–	319 (15%)
Dementia (AD or non-AD)	1,244 (35%)	–	–	–	–	1,244 (58%)

CN = cognitively normal, SCD = subjective cognitive decline, MCI = mild cognitive impairment, AD = Alzheimer's disease, EMIF-AD 90+ = European Medial Information Framework-Alzheimer's Disease 90+ study, EPAD-LCS = European Prevention of Alzheimer's Dementia Longitudinal Cohort Study, ADC = Amsterdam Dementia Cohort.

descriptive information about the two study samples, as well as the total study sample. Individuals from the memory clinic sample were older ($t(2179) = -2.47$, $p = 0.01$), lower educated ($\chi^2(1) = 247.35$, $p < 0.001$), more often male ($\chi^2(1) = 227.85$, $p < 0.001$) and performed significantly worse on the A-IADL-Q ($t(3271) = 59.39$, $p < 0.001$) compared to the CN sample. Table S1 shows the participant count per cohort across different age categories.

The normative model

Visual inspection of the histogram plot of the A-IADL-Q T-scores in the normative sample showed a left skew of the data (Figure S2), resembling a beta distribution with alpha = 2 and beta = 8 parameters. Hence, the beta distribution was used for fitting GAMLSS.

We found that a GAMLSS with an interaction effect between education and a cubic spline for age was the best model for our normative sample (GAIC = −4946.624, $\log(\sigma) = -2.38$) (Table S2). Figure S3 shows the relationships between IADL functioning, age, and educational attainment. Our results show that A-IADL-Q performance generally decreases with age (albeit in a cubic-fashion). The interaction effect with educational attainment indicates that the effect of age on A-IADL-Q is dependent on it. Indeed, older participants with low educational attainment had lower A-IADL-Q scores compared to older participants with medium/high educational attainment. Furthermore, educational attainment is positively associated with A-IADL-Q, meaning that participants with medium/high educational attainment perform better on the A-IADL-Q than those with low educational attainment (Table S2, Figure S3).

The smooth functions used for fitting the cubic spline for age are displayed in the term plots (Figure S4). Figure S5 shows the Worm plot of the residuals, which indicates that the beta distribution does not adequately fit the data.

Cross-validation

The generalizability of the normative model was tested by comparing its global deviance (i.e., a goodness of fit measure, equal to −2*LogLikelihood) with the global deviance after $k = 10$-fold cross-validation. The difference was only 0.48% (global deviance = −4960.623, cross-validated global deviance = −4936.66), indicating that our normative model is highly generalizable to the general population.

The optimal cutoff value for CN versus dementia

For the demographically adjusted A-IADL-Q norm scores, we estimated the optimal cutoff value to distinguish CN from dementia, based on the highest Youden index. We found this cutoff to be -1.85 SD from the population mean (AUC = 0.97; 95%CI [0.96, 0.98]; sensitivity = 90.43%; specificity = 93.89%) (Table S3, Figure S7).

Figure S6 demonstrates the density distribution of the demographically adjusted norm scores in the CN reference population, as well as in the SCD, MCI and dementia groups. The high accuracy of the optimal cutoff to distinguish between CN and dementia is supported by the fact that 94.25% of CN individuals had demographically adjusted norm scores above this cutoff (indicating good performance), compared to only 7.59% of individuals with dementia. The percentage of MCI individuals scoring above the optimal cutoff was 30.55%, and for SCD this was 50.70%.

Diagnostic accuracies corresponding to the optimal cutoff value

We also studied the diagnostic accuracies of the CNvsDem cutoff (which is −1.85SD from population mean, see above) for other diagnostic contrasts (Table S3). This cutoff appeared just as sensitive in distinguishing CN from dementia as in distinguishing SCD and MCI from dementia (sensitivity = 90.43% for all three diagnostic contrasts), although with lower specificity: 49.16% for SCDvsDem, and 31.03% for MCIvsDem, compared to 93.81% for CNvsDem. Moreover, using the −1.85SD cutoff to distinguish CN and SCD individuals from those with MCI resulted in a lower sensitivity (68.97% for both), as well as lower specificity for the SCDvsMCI contrast (specificity = 49.16%). For CNvsMCI, however, the specificity remained the same (specificity = 93.89%). Figure S7 shows the corresponding ROC curves.

Normative data

Figure 1 illustrates our normative model. Individual deviations from the norm are reflected by different percentile categories

https://doi.org/10.1017/S1355617724000031 Published online by Cambridge University Press

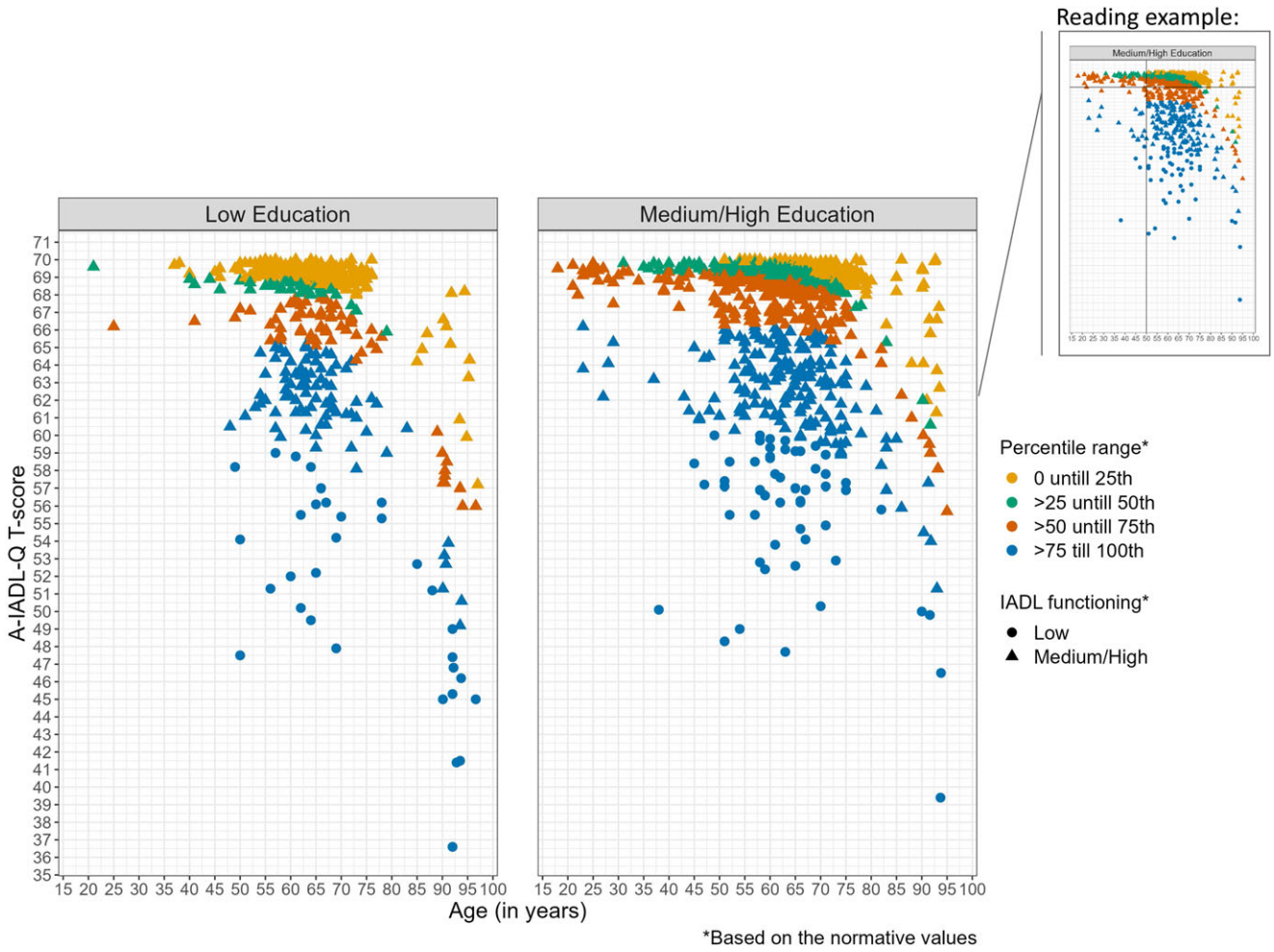

Figure 1. Illustration of the normative model. This figure shows the A-IADL-Q T-score distribution in the normative sample across age, split by educational attainment. *Left*: < 13 years of education, or Dutch Verhage scales 1-5. *Right*: ≥13 years of education, or Dutch Verhage scales 6–7. The different colors indicate the different percentile categories individuals can fall into, with lower percentile scores (*yellow*) reflecting better IADL functioning, as compared to the normal sample. The different shapes indicate the expected level of IADL functioning (i.e., low [*triangle*], or medium/high [*circle*]), based on the optimal cutoff for dementia. *Reading example:* The top right shows a reading example for a 50-year individual with medium/high education and an A-IADL-Q T-score of 68. The place where the two solid lines cross each other indicates the place where this person falls within the normal sample. That is, within the third percentile category, meaning that 50%–75% of cognitively normal individuals score the same or better on the A-IADL-Q than this person. The cutoff for this person (*triangle*) suggests medium/high IADL functioning.

(indicated with different colors), which can be deduced from reading the figure. Moreover, the cutoff for low vs medium/high IADL functioning (indicated with different shapes) can be read.

Discussion

The current study aimed at establishing demographically adjusted norm scores for the A-IADL-Q and providing a corresponding cutoff for dementia, thereby easing results interpretation and accordingly clinical use of the A-IADL-Q.

To our knowledge, this is the first study to establish norm scores for an IADL instrument. For other IADL measures, like the Functional Activities Questionnaire (FAQ) (Pfeffer et al., 1982), Everyday Cognition (ECog) (Farias et al., 2008), and the Alzheimer's Disease Cooperative Study ADL scale (ADCS-ADL) (Fish, 2011), normative values, as well as a norm-based diagnostic cutoffs, have not yet been computed.

While cutoffs for different diagnostic contrasts can be of interest, we only present a single cutoff value here, to avoid possible confusion due to multiple cutoff values. Moreover, our cutoff for dementia showed sufficient diagnostic accuracies for the other diagnostic contrasts examined (all AUC > 0.6), such that one single cutoff suffices.

Notably, a prior A-IADL-Q study has calculated the optimal cutoff for dementia based on the raw A-IADL-Q T-scores (Sikkes et al., 2013). This value (= 51.4), however, had 16% lower sensitivity and 30% lower specificity compared to our norm-based cutoff, and did not take into account age, sex or educational attainment. Clinicians are therefore recommended to use the norm-based cutoff we present here.

We used GAMLSS – a regression-based parametric norming method – for the computation of norm scores, which has two benefits over other types of continuous norming (i.e., semi-parametric and inferential norming): (1) it has readily available statistical criteria for model selection and assessment and (2) it does not require discretization of continuous norm predictors, which possibly introduces imprecision (Timmerman et al., 2021). A known downside of regression-based norming, however, is that the shape of the data must be modeled with any of the available distribution functions, which might not optimally model the shape of the data. This is particularly problematic in the case of large floor or ceiling effects, which cannot be captured well by parametric

https://doi.org/10.1017/S1355617724000031 Published online by Cambridge University Press

distributions (Lenhard et al., 2019). A floor or ceiling effect exists when, respectively, less or more than 20% of the participants have the maximum score on an instrument (Garin, 2014). While our data showed a left skew, only 17% of individuals had a T-score >= 69.5, supporting the absence of a ceiling effect, and advocating for regression-based norming.

The best normative model comprised a cubic spline for age and its interaction with educational attainment. Sex appeared not to be a determinant of IADL functioning, in line with a prior study on differential item functioning of the A-IADL-Q across eight countries (Dubbelman et al., 2020). Nevertheless, sex differences in IADL have been reported in Europe (Scheel-Hincke et al., 2020). Those differences were significantly larger in Southern compared to Northern Europe (Scheel-Hincke et al., 2020), which may suggest that our normative sample more closely represents Northern Europe. Indeed, most of our normative sample is from the Netherlands, so some caution is warranted when the model is applied to non-Northern Europeans.

To make our norm scores applicable to a broader, European population, we have included European data from the EPAD-LCS cohort, which is an important strength of our study, because it increases generalizability of our results. Furthermore, we included a cohort of cognitively healthy nonagenarians, which further adds to the generalizability of results, by increasing applicability of our normative sample to older individuals. Other strengths of this study are the broad age range of our normative sample (18y–97y) and its large sample size(n > 1,000).

One limitation of our study is that the Worm plot indicated bad model fit. Be that as it may, these normative values are computed using the highly flexible GAMLSS framework, which is in many ways superior to the traditional(mean-based) standard polynomial regression approach. Thus, even though our data did not fit the beta distribution well, it is the best fit we could have obtained without subjecting our data to complex transformations (e.g., a square- or cube root), which come with their own limitations. Another limitation is that our normative data are not directly accessible. Hence, we are currently exploring the implementation of an A-IADL-Q norm score calculator in existing tools for research and clinical use, such as ADappt (van Maurik et al., 2019). Finally, our normative data are limited to a European population. Future studies should therefore include participants from different continents, cultures, and socioeconomic backgrounds, in order to facilitate world-wide use of the A-IADL-Q norm data in the clinic.

Conclusion

To conclude, we present norm scores for the A-IADL-Q and provide an optimal cutoff for dementia. Our data are key to improving clinical assessment of IADL performance, as they allow for easier interpretation of scores.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1355617724000031.

Acknowledgments. The authors would like to thank all study participants, as well as everyone involved in data collection and data sharing.

Funding statement. The Amsterdam IADL Questionnaire is free for use in all public health and not-for-profit agencies and can be obtained via https://www.alzheimercentrum.nl/professionals/amsterdam-iadl. The development of the Amsterdam IADL Questionnaire is supported by grants from Stichting VUmc Fonds and Innovatiefonds Zorgverzekeraars.

This work was supported by public–private funding of which SAMS was the recipient. She received funding from Health-Holland, Topsector Life Sciences & Health (PPPallowance; LSHM20084-SGF, project DEFEAT-AD), and the National Institutes of Health, as well as license fees from Green Valley, VtV Therapeutics, Alzheon, Vivoryon, and Roche, and honoraria from Boehringer, Toyama and Biogen. All funding is paid to her institution. In addition, the work was supported by license fees from Brain Research Center Holding BV obtained from the for-profit commercial use licensing of the Amsterdam IADL Questionnaire to third-party clients.

Research of Alzheimer Center Amsterdam is part of the neurodegeneration research program of Amsterdam Neuroscience. Alzheimer Center Amsterdam is supported by Stichting Alzheimer Nederland and Stichting Steun Alzheimercentrum Amsterdam. The chair of Wiesje van der Flier is supported by the Pasman stichting. The clinical database structure was developed with funding from Stichting Dioraphte.

The Dutch Brain Research Registry (Hersenonderzoek.nl) is supported by ZonMw-Memorabel (project no 73305095003), Alzheimer Nederland, Amsterdam Neuroscience, and Hersenstichting (Dutch Brain Foundation).

The EMIF-AD 90+ Study was funded by the EU/EFPIA Innovative Medicines Initiative Joint Undertaking EMIF grant agreement no. 115372.

The European Prevention of Alzheimer's Dementia project was funded by the Innovative Medicines Initiative grant agreement 115736.

Competing interests. MCP, MAD, JC, CR, MV, LV, PV, and MDZ report no disclosures relevant to the manuscript.

WMF has received further funding from NWO, EU-FP7, EU-JPND, Alzheimer Nederland, CardioVasculair Onderzoek Nederland, Stichting Dioraphte, Gieskes-Strijbis fund, Stichting Equilibrio, Pasman Stichting, Biogen MA Inc., Boehringer Ingelheim, Life-MI, AVID, Roche BV, Fujifilm, and Combinostics. W.M. van der Flier holds the Pasman chair, has performed contract research for Biogen MA Inc. and Boehringer Ingelheim, is a consultant to Oxford Health Policy Forum CIC, Roche and Biogen MA Inc., and has been an invited speaker at Boehringer Ingelheim, Biogen MA Inc., Danone, Eisai, WebMD Neurology (Medscape). All funding is paid to her institution.

SAMS co-developed the A-IADL-Q, which is freely available for use by academic users and not-for-profit organizations. License fees from for-profit organizations are paid to her institution. SAMS was supported by grants from JPND and Zon-MW and has provided consultancy services in the past 2 years for Nutricia and Takeda. All funds were paid to her institution.

References

Dubbelman, M. A., Verrijp, M., Facal, D., Sánchez-Benavides, G., Brown, L. J. E., der Flier, W. M., Jokinen, H., Lee, A., Leroi, I., Lojo-Seoane, C., Milošević, V., Molinuevo, J. L. D., Pereiro Rozas, A. X., Ritchie, C., Salloway, S., Stringer, G., Zygouris, S., Dubois, B., Epelbaum, S., Scheltens, P., & Sikkes, S. A. M. (2020). The influence of diversity on the measurement of functional impairment: An international validation of the Amsterdam IADL questionnaire in eight countries. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, *12*(1), e12021. https://doi.org/10.1002/dad2.12021

Farias, S. T., Mungas, D., Reed, B. R., Cahn-Weiner, D., Jagust, W., Baynes, K., & Decarli, C. (2008). The measurement of everyday cognition (ECog): Scale development and psychometric properties. *Neuropsychology*, *22*(4), 531–544. https://doi.org/10.1037/0894-4105.22.4.531

Fish, J. (2011). Alzheimer's disease cooperative study ADL scale. In J. S. Kreutzer, J. DeLuca, & B. Caplan (Eds.), *Encyclopedia of clinical neuropsychology* (pp. 111–112). Springer New York.

Garin, O. (2014). Ceiling effect. In A. C. Michalos (Eds.), *Encyclopedia of quality of life and well-being research* (pp. 631–633). Springer Netherlands.

Jutten, R. J., Peeters, C. F. W., Leijdesdorff, S. M. J., Visser, P. J., Maier, A. B., Terwee, C. B., Scheltens, P., & Sikkes, S. A. M. (2017). Detecting functional decline from normal aging to dementia: Development and validation of a short version of the Amsterdam IADL questionnaire. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, *8*(1), 26–35. https://doi.org/10.1016/j.dadm.2017.03.002

Koster, N., Knol, D. L., Uitdehaag, B. M., Scheltens, P., & Sikkes, S. A. (2015). The sensitivity to change over time of the Amsterdam IADL

questionnaire(©). *Alzheimers & Dementia*, *11*(10), 1231–1240. https://doi.org/10.1016/j.jalz.2014.10.006

Legdeur, N., Badissi, M., Carter, S. F., de Crom, S., van de Kreeke, A., Vreeswijk, R., Trappenburg, M. C., Oudega, M. L., Koek, H. L., van Campen, J. P., Keijsers, C. J. P. W., Amadi, C., Hinz, R., Gordon, M. F., Novak, G., Podhorna, J., Serné, E., Verbraak, F., Yaqub, M., Hillebrand, A., Griffa, A., Pendleton, N., Kramer, S. E., Teunissen, C. E., Lammertsma, A., Barkhof, F., van Berckel, B. N. M., Scheltens, P., Muller, M., Maier, A. B., Herholz, K., & Visser, P. J. (2018). Resilience to cognitive impairment in the oldest-old: Design of the EMIF-AD 90+ study. *BMC Geriatrics*, *18*(1), 289. https://doi.org/10.1186/s12877-018-0984-z

Lenhard, A., Lenhard, W., Gary, S., & Christensen, K. B. (2019). Continuous norming of psychometric tests: A simulation study of parametric and semi-parametric approaches. *PLoS One*, *14*(9), e0222279. https://doi.org/10.1371/journal.pone.0222279

Marquand, A. F., Rezek, I., Buitelaar, J., & Beckmann, C. F. (2016). Understanding heterogeneity in clinical cohorts using normative models: Beyond case-control studies. *Biological Psychiatry*, *80*(7), 552–561. https://doi.org/10.1016/j.biopsych.2015.12.023

Pfeffer, R. I., Kurosaki, T. T., Harrah, C. H.Jr, Chance, J. M., & Filos, S. (1982). Measurement of functional activities in older adults in the community. *Journals of Gerontology*, *37*(3), 323–329. https://doi.org/10.1093/geronj/37.3.323

Rigby, R. A., & Stasinopoulos, D. M. (2005). Generalized additive models for location, scale and shape. *Journal of the Royal Statistical Society Series C-Applied Statistics*, *54*(3), 507–544. https://doi.org/10.1111/j.1467-9876.2005.00510.x

Ritchie, C. W., Molinuevo, J. L., Truyen, L., Satlin, A., Van der Geyten, S., & Lovestone, S. (2016). Development of interventions for the secondary prevention of Alzheimer's dementia: The European prevention of Alzheimer's dementia (EPAD) project. *The Lancet Psychiatry*, *3*(2), 179–186. https://doi.org/10.1016/s2215-0366(15)00454-x

Scheel-Hincke, L. L., Möller, S., Lindahl-Jacobsen, R., Jeune, B., & Ahrenfeldt, L. J. (2020). Cross-national comparison of sex differences in ADL and IADL in Europe: Findings from SHARE. *European Journal of Ageing*, *17*(1), 69–79. https://doi.org/10.1007/s10433-019-00524-y

Sikkes, S. A., Knol, D. L., Pijnenburg, Y. A., de Lange-de Klerk, E. S., Uitdehaag, B. M., & Scheltens, P. (2013). Validation of the Amsterdam IADL questionnaire©, a new tool to measure instrumental activities of daily living in dementia. *Neuroepidemiology*, *41*(1), 35–41. https://doi.org/10.1159/000346277

Sikkes, S. A., Pijnenburg, Y. A., Knol, D. L., de Lange-de Klerk, E. S., Scheltens, P., & Uitdehaag, B. M. (2013). Assessment of instrumental activities of daily living in dementia: Diagnostic value of the Amsterdam instrumental activities of daily living questionnaire. *Journal of Geriatric Psychiatry and Neurology*, *26*(4), 244–250. https://doi.org/10.1177/0891988713509139

Thiele, C., & Hirschfeld, G. (2021). Cutpointr: Improved estimation and validation of optimal cutpoints in R. *Journal of Statistical Software*, *98*(11), 1–27. https://doi.org/10.18637/jss.v098.i11

Timmerman, M. E., Voncken, L., & Albers, C. J. (2021). A tutorial on regression-based norming of psychological tests with GAMLSS. *Psychological Methods*, *26*(3), 357–373. https://doi.org/10.1037/met0000348

van der Flier, W. M., & Scheltens, P. (2018). Amsterdam dementia Cohort: Performing research to optimize care. *Journal of Alzheimers Disease*, *62*(3), 1091–1111. https://doi.org/10.3233/jad-170850

van Maurik, I. S., Visser, L. N. C., Pel-Littel, R. E., van Buchem, M. M., Zwan, M. D., Kunneman, M., Pelkmans, W., Bouwman, F. H., Minkman, M., Schoonenboom, N., Scheltens, P., Smets, E. M. A., & van der Flier, W. M. (2019). Development and Usability of ADappt: Web-based tool to support clinicians, patients, and caregivers in the diagnosis of mild cognitive impairment and Alzheimer disease. *JMIR Formative Research*, *3*(3), e13417. https://doi.org/10.2196/13417

Voncken, L., Albers, C. J., & Timmerman, M. E. (2019). Model selection in continuous test norming with GAMLSS. *Assessment*, *26*(7), 1329–1346. https://doi.org/10.1177/1073191117715113

Zwan, M. D., van der Flier, W. M., Cleutjens, S., Schouten, T. C., Vermunt, L., Jutten, R. J., van Maurik, I. S., Sikkes, S. A. M., Flenniken, D., Howell, T., Weiner, M. W., Scheltens, P., & Prins, N. D. (2021). Dutch brain research registry for study participant recruitment: Design and first results. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*, *7*(1), e12132. https://doi.org/10.1002/trc2.12132

https://doi.org/10.1017/S1355617724000031 Published online by Cambridge University Press