Open-Source Personality Trait Norms for the United Kingdom and Ireland

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Abstract: Most copyrighted personality inventories facilitate norm-referencing through illustrative tables, yet their application to the many fields relevant to personality measurement is constrained by the need for stakeholders to possess the requisite financial resources to access them. Using an IPIP-NEO-300 dataset from Johnson's IPIP-NEO data repository, we created open-source norm tables for different age groups (14–17 years; 18–25 years; and 30+ years) within a combined standardization sample from the United Kingdom (UK) and Ireland (N = 18,591). The newly created tables are freely available online (https://osf.io/tbmh5), and there is no need to ask for permission to modify them. We provide general instructions that can be used to create open-source personality trait norms for other countries, settings, and age groups, as well as gender-specific norms. There is great potential for these norms to be used in various settings and their open-source freedoms may encourage future collaborations and investigations.

Keywords: five-factor model, International Personality Item Pool, IPIP, norm-referencing, open-source

OPEN DATA OPEN MATERIALS

Developed by members of the (public domain) International Personality Item Pool (IPIP) scientific collaboratory, the IPIP-NEO-300 (Goldberg et al., 2006) is a 300-item representation of the NEO Personality Inventory (NEO PI-R; Costa & McCrae, 1992), itself a "gold-standard" measure of the Five-Factor Model (FFM) of personality (Johnson, 2017). Unlike its predecessor and other copyrighted personality measures, the IPIP-NEO-300 is freely accessible on the Internet, and it is possible to inspect and modify scoring keys and content without publisher permission. The "open-source" freedoms afforded to the IPIP-NEO-300 reflect the growing movement across many scientific fields towards greater methodological transparency, largely unrestricted access to data protocols and products of research, and open collaboration between research networks in the absence of centralized or hierarchical governance structures (Vicente-Saez & Martinez-Fuentes, 2018; Woelfle et al., 2011). They also reflect considerable efforts to accelerate progress in the science of personality measurement, previously impeded by the predominance of copyrighted personality inventories developed by publishers who – owing to their vested commercial interests (and perhaps owing to a willingness to protect the public from misuse) – have disallowed and/or discouraged free-of-charge and open scientific collaboration, particularly with respect to the experimentation with, and sharing of, inventories and their underlying data (Goldberg et al., 2006).

There are various signs that the increasing adoption of open source principles is contributing to accelerated progress within personality measurement: the IPIP-NEO-300 has been extensively accessed around the world via the Internet; it has been translated into multiple languages; several shorter versions have been developed including the IPIP-NEO-120 (Johnson, 2014) and the Mini-IPIP (Donnellan et al., 2006); multiple alternative public domain personality inventories have been formulated including the Big Five Aspects Scales (DeYoung et al., 2007), the Big Five Inventory-2 (Soto & John, 2017), and the Five-Factor Model Questionnaire (Gill & Hodgkinson, 2007); hundreds of published investigations surrounding the FFM and similar personality concepts have been facilitated, and the psychometric properties of various IPIP-derived measures have been closely examined (see https://ipip.ori.org/newPublications.htm for a periodically updated list of references).

The application of open-source principles to the IPIP-NEO-300 and similar public domain personality inventories

https://doi.org/10.1027/1015-5759/a000644

has also facilitated the creation of vast data repositories derived from online respondents. One example is John A. Johnson's IPIP-NEO data repository (https://osf.io/tbmh5/), freely accessible online and based on the anonymized responses of nearly one million individuals who completed the IPIP-NEO-300 or the shorter IPIP-NEO-120 at another website managed by Johnson (https://www.personal.psu.edu/~j5j/IPIP/; Johnson, 2005, 2014). A major benefit of the repository is the facilitation of research with enormous sample sizes; for example, in investigations of gender and cross-cultural differences in personality profiles (Kajonius & Johnson, 2018; Kajonius & Mac Giolla, 2017), examinations of the robustness of personality types (Freudenstein et al., 2019; Gerlach et al., 2018) and in research on age differences in personality (Kajonius & Johnson, 2019).

We demonstrate in the current article that Johnson's IPIP-NEO data repository also facilitates open-source norm-referencing. Norm-referencing encompasses the comparison of individual scores with the distribution of scores from a standardization sample, providing insight into individual differences in personality traits and abilities. Most copyrighted personality inventories incorporate norm-referencing through illustrative tables, yet their application to the many fields relevant to personality measurement (e.g., clinical and counseling psychology, occupational psychology, educational psychology, and consumer behavior) is constrained by the need for stakeholders to possess the requisite financial resources to access them. Another issue with copyrighted norms tables is that updates do not always keep pace with the latest developments in personality research (Goldberg et al., 2006); for example, existing adult norms are rarely categorized by age group despite copious findings indicating that personality tends to change across the lifespan (Chopik & Kitayama, 2018; Helson & Wink, 1992; Lucas & Donnellan, 2011; McCrae et al., 1999, 2000; Roberts et al., 2005, 2006). There is also the problem of geography: norms for many countries and regions are currently unavailable. This seems an important omission since localized norms arguably offer greater validity than international or global norms applied to local regions, and given the evidence for (small) cross-cultural differences in Big Five traits (Kajonius & Mac Giolla, 2017; Rentfrow & Gosling, 2013; Rentfrow et al., 2015). We address these issues in the current article, by our reporting on our creation of open-source norm tables for varying age groups within a combined standardization sample from the United Kingdom (UK) and Ireland – neighboring countries with similar cultural norms, and health systems. We also provide general instructions that can be used to create IPIP-NEO norms for other countries (or indeed a global sample) and age groups.

Methods

Dataset for Norm Creation

We used the global IPIP-NEO-300 dataset (N = 307,313; M_{age} = 25.2 [SD = 10.00]; 60.2% female); available on Johnson's IPIP-NEO data repository (https://osf.io/tbmh5). The steps involved in the creation of the repository are documented elsewhere (Johnson, 2005, 2014; Kajonius & Mac Giolla, 2017); yet it is worth noting that data were collected between January 31, 2001, and May 16, 2011. As outlined above, localized personality trait norms might offer greater validity than global norms. We therefore focused on localized norms, selecting a combined UK and Ireland standardization sample (combined N = 18,591; UK N = 16,489; Ireland N = 2,102). The sample's mean age was 25.1 years (SD = 9.94), the age range was 10–77 years, and 54% of participants were female.

We decided to combine data from the UK and Ireland in order to maximize the pooled sample size (particularly relevant for the Irish sample which by itself was relatively small). This decision took into account the close proximity of the UK and Ireland, and their similar cultural norms, laws, and health systems. It also took into account the precursory finding of only slight personality trait differences between the two countries. Here, all standardized mean differences were below the conventional d = 0.2 cut-off point for a "small effect size" (Cohen, 1988): Openness (d = 0.001; 95% CI [−0.04, 0.04]); Conscientiousness (d = 0.15; 95% CI [0.10, 0.20]); Extroversion (d = 0.08; 95% CI [0.04, 0.13]); Agreeableness (d = 0.16; 95% CI [0.11, 0.20]); Neuroticism (d = 0.12; 95% CI [0.08, 0.17]). It is noted that t-tests indicated significant between-country differences for four of the five traits; however, the likelihood of statistical significance is indicated in analyses involving very large sample sizes is relatively high, and therefore effect size calculations are widely considered to be more informative (Lin et al., 2013; Sullivan & Feinn, 2012).

Measures

Comprising 300 items, scale development studies of the IPIP-NEO-300 indicate high internal consistency (mean Cronbach's α = 0.8) and a strong association with the NEO PI-R (Costa & McCrae, 1992), evidenced by a mean Pearson's correlation of r = 0.73; which rises to 0.94 when corrected for attenuation (Goldberg et al., 2006; Johnson, 2014). Scores on the IPIP-NEO-300 and shorter versions correlate with health behaviors, anxiety, depression, and other clinically-important outcomes (Goldberg et al., 2006; Hagger-Johnson & Whiteman, 2007; Johnson, 2014; Sutton et al., 2011). The 300 items on the IPIP-NEO-300 are scored from 1 to 5. There are 60 items for each of the "Big Five" personality traits, with 10 items dedicated to 6 personality facets (or sub-traits) underlying each trait. Possible scores on the trait scales range from 60 to 300; possible scores on the facets scales range from 10 to 50.

Dataset Management

From the combined UK and Ireland sample, we selected three subsamples based on age: 14–17 years (n = 3,466; M_{age} = 15.8 years, SD = 1.01); 18–29 years (n = 10,032; M_{age} = 21.8 years, SD = 3.26), and 30 years and over (n = 4,808; M_{age} = 39.4 years, SD = 7.86). The first age group represents what we term "middle adolescence": 4 years in the middle of the recently recommended 10–24 age range for adolescence (Sawyer et al., 2018) that are below the European legal adult age of 18. The second age group represents "emerging adulthood" (Arnett, 2014; Arnett et al., 2014); and the final age group represents those remaining (older) adults, hereafter referred to as "established adulthood." The decision to exclude adolescents under the age of 14 took into account findings indicating that both meta-cognitive and self-reflective abilities (which are likely to be important for accurate self-report personality assessment) greatly increase throughout adolescence and are, therefore, on average, relatively low in younger adolescents (Sebastian et al., 2008; Weil et al., 2013). The decision to formulate separate norms for middle adolescence and adulthood reflects differences in developmental periods, social norms, service configurations, and legal status. The decision to divide the adult age-groups into emerging adulthood (18–29 years) and established adulthood (30 years and older) was made for two reasons. First, there is good support for the theory that emerging adulthood encompasses a specific developmental stage of adulthood, mainly because it is a time particularly characterized by profound identity exploration, instability (e.g., in relationships, education, and work), self-focus, transition, and optimism (Arnett, 2014; Arnett et al., 2014). Second, the intention was to account for increasingly robust cross-cultural evidence for continuous personality change across the lifespan; for example, positive age associations for agreeableness, conscientiousness, and emotional stability, and negative age associations for openness and extroversion have been widely reported (Chopik & Kitayama, 2018; Damian et al., 2019; Donnellan & Lucas, 2008; Helson & Wink, 1992; Lucas & Donnellan, 2011; McCrae et al., 1999, 2000; Roberts et al., 2005, 2006). We explored the possibility of further dividing the established adulthood group into subgroups (e.g., 65 years and older) but this would have been at the expense of statistical power since available data for older adults were limited.

Differences in personality trait scores across three chosen age groups were first analyzed using a one-way MANOVA that estimated between-group differences for the combination of the Big Five personality traits; following this, between-group differences in specific traits were analyzed by comparing means and 95% confidence intervals and reporting effect sizes. Here, the significance level was not adjusted for multiple comparisons (e.g., using a Bonferroni correction): it was deemed unnecessary because p-values offer limited interpretive utility in very large sample sizes and thus the focus should arguably be on effect sizes and their accompanying confidence intervals (Lin et al., 2013; Sullivan & Feinn, 2012).

Due to limited time resources, we decided not to additionally create gender-specific norms; however, it is possible for others to create such norms by downloading the IPIP-NEO-300 dataset from Johnson's IPIP-NEO data repository (https://osf.io/tbmh5), implementing our freely available data management protocols – conducted on STATA 13 (StataCorp LP, College Station, TX, USA; also available on the data repository; Electronic Supplementary Material, ESM 1) – and following our below instructions. Norms for different countries could be similarly produced, though it is worth noting that data covering the UK's individual member countries (England, Scotland, Wales, and Northern Ireland) are currently not available within Johnson's data repository.

Creation of Norms

In personality inventory research and development, there exists a considerable consensus that ± 0.5 SDs of the mean for a standardization sample can be labeled as "average" and scores outside that range as "low" or "high" (Hofstee & de Raad, 1992; Johnson, 2019). Developers of many popular personality inventories – such as the NEO PI-R (Costa & McCrae, 1992) – have complemented the ± 0.5 SD convention for the average range by adding ± 1.5 SD outer boundaries for "high" and "low" ranges, leaving remaining values representative of extremes (very high or very low). Primarily to facilitate the comparability of our norms to those from popular personality inventories we followed both the ± 0.5 SD convention and the NEO PI-R procedure in the creation of our norms. As noted by Johnson (2019), the ± 0.5 convention is somewhat arbitrary, yet it allows ~38% of normally distributed scores to be considered as "average," facilitating the nuanced differentiation of personality profiles, in contrast to an alternative ± 1.0 SD cut-off point which classes ~67% of the sample as "average" (Schuerger, Powers, & Franklin, 1977), and another method based on statistical significance whereby a ± 1.4 SD cut-off point classes ~86% of the sample as "average" (Hofstee & de Raad, 1992). The ranges provided in our norms offer an additional interpretive advantage (that is availed of in our norms tables): they can be mapped to intuitive *T*-score ranges; for example, the ± 0.5 *SD* "average range" corresponds to a range of $T = 45$ to $T = 55$ (Johnson, 2019). We, therefore, deployed the following ranges for norms, with calculation procedures also listed:

- Average range upper boundary = +0.5 *SD* of the mean. Calculation: mean + (*SD* × 0.5); round result *down* to nearest whole number regardless of decimal value.
- Average range lower boundary = −0.5 *SD* of the mean. Calculation: mean − (*SD* × 0.5); round result *up* to nearest whole number regardless of a decimal value.
- High range upper boundary = 1.5 *SD* of the mean. Calculation: mean + (*SD* × 1.5); round result *down* to nearest whole number regardless of a decimal value.
- Low range lower boundary = −1.5 *SD* of the mean. Calculation: mean − (*SD* × 1.5); round result *up* to nearest whole number regardless of a decimal value.
- Very high range = remaining values above the "high" range upper boundary.
- Very low range = remaining values below the "low" range upper boundary.

We automated the above calculations using a Microsoft Excel spreadsheet (ESM 2).

Creation of Norm Tables

For each of the three age groups, we utilized Microsoft Word in the creation of norm tables that cover all of the Big Five personality traits and the 30 facets. The design of the tables was constrained by text legibility concerns, and the amount of space available on "A3" paper, a common page format for norms tables, and a standard document presentation option in computer "style sheet languages." On the normal distribution curve, ~38% of data are contained within the parameters of our selected "average" range, ~24% of data are contained within each of our "high" and "low" ranges (~48% across the two ranges), and ~7% of data are contained within each of our "very high" and "very low" ranges (~14% across the two ranges). To mirror this distribution in our norms tables, we considered allocating 38 rows to the average range, 24 rows to each of the high and low ranges, and 7 rows to each of the very high and very low ranges; however, we decided against this due to aforementioned text legibility concerns and space restrictions. Aiming for the best possible alternative, we instead allocated ~50% of these amounts of rows to each range: 19 rows for the average range, 12 rows to each of the high and low ranges, and 4 rows to each of the remaining two ranges. This procedure produced legible tables that proportionally represented the relevant ranges of the normal curve.

Where possible, symmetry was aimed for in the display of scores, to reflect the symmetry in the normal curve distribution. Limited space meant that some score ranges (e.g., "250–253") rather than individual scores (e.g., "250," "251," "252," "253") had to be included. All score ranges were displayed in equal intervals within each category; when they could not be split into equal intervals, the range of scores in the center row(s) was either lengthened or shortened. When symmetry could not be achieved by altering the range of scores in the center row(s), score ranges in the outer rows within each category were shortened (as those rows are furthest away from the center of the normal distribution where most data are concentrated). Relatedly, the number of available rows occasionally prevented the symmetrical presentation of scores; in these cases, a greater proportion of data were presented in rows closest to the center of the normal distribution.

Results

Means, standard deviations, and norms for the specified age ranges of the UK and Ireland standardization sample are provided in the supplementary Microsoft Excel file (ESM 2). The one-way MANOVA indicated a significant difference across age groups for the combination of the Big Five personality traits, $F(2, 18{,}304) = 235.07$, $p < .01$. Moreover, there were significant between-age-group mean differences for each of the five personality traits (Table 1). For conscientiousness, agreeableness, and neuroticism, there were significant differences across all age-group comparisons, with larger standardized mean differences between the middle adolescent group and the established adulthood group. Furthermore, conscientiousness and agreeableness tended to increase with age, while neuroticism tended to decrease with age. For openness, the middle adolescence age group scored significantly lower than the two adult age groups; yet there was no significant difference in openness between the adult age groups. For extroversion, the middle adolescence age group scored significantly higher than the established adulthood age group; the emerging adulthood group also scored significantly higher than the established adulthood group. There was no significant mean difference in extroversion between the two younger age groups.

Downloadable norms tables have been made freely available at Johnson's IPIP-NEO data repository (https://osf.io/tbmh5) and samples are also provided in this paper (ESM 3–5). It is important to note that these norms tables – available on an external website (Johnson's IPIP-NEO data repository) – are separate from the current paper; therefore, the norms tables are not affected by any copyright-related restrictions associated with the current paper's publication.

Table 1. Mean differences in personality traits across age groups

Age group (#)	Trait	Mean	*SD*	95% LCI	95% UCI	Interpretation*
14–17 years (1)	Openness	220.46	26.18	219.59	221.34	Significant differences between groups 1 and 2 (*d* = 0.15; 95% CI [0.11, 0.19)], and groups 1 and 3 only (*d* = 0.18; 95% CI [0.14, 0.22]).
18–29 years (2)	Openness	224.36	25.55	223.86	224.87	
30+ years (3)	Openness	225.37	26.83	224.61	226.13	
14–17 years (1)	Conscientiousness	189.18	30.85	188.16	190.21	Significant differences between groups 1 and 2 (*d* = 0.31; 95% CI = 0.28-0.35), groups 1 and 3 (*d* = 0.83; 95% CI [0.78, 0.87]), and groups 2 and 3 (*d* = 0.51; 95% CI [0.47, 0.55]).
18–29 years (2)	Conscientiousness	199.00	30.72	198.40	199.60	
30+ years (3)	Conscientiousness	214.78	30.74	213.91	215.64	
14–17 years (1)	Extroversion	202.80	33.71	201.68	203.93	Significant differences between groups 1 and 3 (*d* = 0.19; 95% CI [0.14, 0.23]), and groups 2 and 3 only (*d* = 0.17; 95% CI [0.13, 0.21]).
18–29 years (2)	Extroversion	202.15	32.92	201.51	202.79	
30+ years (3)	Extroversion	196.39	34.03	195.43	197.35	
14–17 years (1)	Agreeableness	201.54	30.10	200.54	202.54	Significant differences between groups 1 and 2 (*d* = 0.25; 95% CI [0.21, 0.39]), groups 1 and 3 (*d* = 0.41; 95% CI [0.37, 0.46]), and groups 2 and 3 (*d* = 0.15; 95% CI [0.12, 0.19]).
18–29 years (2)	Agreeableness	208.89	28.86	208.32	209.45	
30+ years (3)	Agreeableness	213.34	26.80	212.58	214.10	
14–17 years (1)	Neuroticism	185.94	37.00	184.71	187.18	Significant differences between groups 1 and 2 (*d* = 0.13; 95% CI [0.09, 0.17]), groups 1 and 3 (*d* = 0.39; 95% CI [0.39, 0.48]), and groups 2 and 3 (*d* = 0.31; 95% CI [0.27, 0.34]).
18–29 years (2)	Neuroticism	180.84	37.53	180.11	181.58	
30+ years (3)	Neuroticism	168.86	40.54	167.71	170.01	

Note. *If 95% confidence intervals (CIs) overlap there is no significant mean difference, and vice versa. LCI = lower confidence interval; UCI = upper confidence interval; *SD* = standard deviation.

Discussion

In contrast to norm-referencing tables contained within copyrighted personality inventories, our IPIP-NEO-300 norm-referencing tables for the UK/Ireland are open-source: they are free-to-use, downloadable at Johnson's IPIP-NEO data repository (https://osf.io/tbmh5), and there is no need to ask for permission to modify them. Although the norms tables only apply to the IPIP-NEO-300 (and not abbreviated versions of the instrument), and to our selected geographic regions and age ranges, we have provided general instructions that can be used in the creation of norms for other open-source personality inventories, countries, and age groups (see Methods section). Overall, both our and modified norms tables could be applied to the many fields relevant to personality measurement (e.g., clinical and counseling psychology, occupational psychology, educational psychology, and consumer behavior). In particular, they could be used to track progress within the growing number of FFM-based programs that aim to foster intentional personality change using specific behavioral goals and tasks (Hudson et al., 2019; Hudson & Fraley, 2015, 2016; Hudson & Roberts, 2014; Martin et al., 2014). Here, any personality change arising from participation could easily be mapped onto the tables.

Our norms are unique in terms of the age groups utilized – most popular norms tables simply categorize by an adult and adolescent age groups. Our decision to utilize the middle adolescence, emerging adulthood, and established adulthood age groups was arguably supported: there were multiple significant between-group differences, involving each of the "Big Five" traits; for example, agreeableness and conscientiousness increased with age, and neuroticism and extraversion (in part) decreased with age. Moreover, these findings are in line with existing evidence and the growing consensus that traits continuously change across the lifespan (Chopik & Kitayama, 2018; Damian et al., 2019; Donnellan & Lucas, 2008; Helson & Wink, 1992; Lucas & Donnellan, 2011; McCrae et al., 1999, 2000; Roberts et al., 2005, 2006).

The above findings should be interpreted with caution. Johnson (2014) discusses methodological issues inherent in his IPIP-NEO repository (e.g., the need to use a protocol for handling inattentive responding, missing data, and insufficient internal consistency). In addition, information about the representativeness of samples contained with the IPIP-NEO repository is limited, as the online respondents only disclose their age, gender, and country alongside responses to the included personality questionnaires. On the other hand, the gender ratio of the overall UK/Ireland sample can be considered representative: 54% were female, compared with the corresponding figure of ~51% from the most recent censuses conducted in both the UK and Ireland. While the convention that ± 0.5 *SD*s of the mean for a standardization sample can be labeled as "average" is widely followed, cut-off points for other norm categories are somewhat arbitrary, and a recent preliminary investigation indicated that an alternative method for cutting scores – optimal discriminant analysis (Yarnold & Soltysik, 2005) – may offer greater precision (Johnson, 2019). The optimal discriminant analysis encompasses an emerging statistical analysis paradigm that aims to maximize (weighted) predictive accuracy in the context of exact distribution theory, and its leading proponents have developed accompanying software (Yarnold & Soltysik, 2005). It was beyond the scope of the current study to integrate optimal discriminant analysis techniques but such integration is similar future studies is worthy of consideration, especially since it appears possible to automate cut-off score calculations using algorithms. Regarding our final limitation, the choice of age groups for the norms tables was partly borne of necessity: there were insufficient data available for older adults. As the methods for norms table creation described in this paper can be freely applied to other open-source personality inventories that have generated open-source data archives (e.g., see https://ipip.ori.org/newNorms.htm), we anticipate that future investigations can feasibly address the above methodological concerns.

The work described within this paper can be thought of as just one of the many contributions to the shared forum for global scientific collaboration afforded by the International Personality Item Pool (Goldberg et al., 2006). We, therefore, encourage other researchers to revise and experiment with our protocols and norm-tables, and they are free to do so without permission, in line with open-source principles. The application of our protocols to the creation of gender-specific IPIP-NEO norms (beyond the scope of the current paper due to time constraints) would be particularly welcome, as gender differences in personality are well-documented (Kajonius & Johnson, 2018, 2019). Collaborative experimentation with the layout and user-friendliness of the norms-tables would also be welcome. Interestingly, during the peer review process, an anonymous reviewer suggested that we use Histograms (with normal distribution curves) to display the norms, and we have followed this suggestion in the creation of Histogram norms applied at the personality trait level (ESM 6).

While our data management protocols were automated, we relied on the manual creation of norms tables – working with basic word processing software. This was very time-consuming and this prevented us from producing additional norms tables (e.g., adjusted for gender). Automatically generated norms tables would undoubtedly benefit future research in terms of efficiency, accuracy, and applicability. Some progress has already been made here: the Histogram norms suggested during the peer review process can be automatically generated by statistical software, and our automated IPIP-NEO-300 scoring tool (see ESM 7) which produces (admittedly primitive) norms tables using Microsoft Excel has been made available on Johnson's IPIP-NEO data repository (https://osf.io/tbmh5).

In conclusion, we reiterate that our open-source personality norms tables could prove useful to those who do not possess the requisite financial resources to access copyrighted versions. On a cautionary note, there is potential for these freely available tables to be erroneously applied or incorrectly interpreted by unqualified persons, in line with general concerns raised by leading personality researchers in relation to IPIP materials (Goldberg et al., 2006). Although evidence for the misuse of IPIP materials is currently scant, few relevant investigations have been undertaken and addressing this gap should arguably constitute a research priority for the wide community of researchers who utilize, promote, or share IPIP materials. We urge the responsible use of our norms tables; in particular, if the tables are to be used for substantive assessment purposes, as distinct for research purposes, users should be suitably qualified, or operate under the direct supervision of a suitably qualified professional.

Finally, it is hoped that our norms tables can be improved upon by other researchers and that our promotion of open-source principles encourages the further collaboration and sharing of data within the science of personality measurement. Accordingly, we reaffirm Johnson's (2014, p. 87) statement that "science is meant to be an open, collaborative endeavor, limited only by the imagination of researchers".

Electronic Supplementary Materials

The electronic supplementary material is available with the online version of the article at https://doi.org/10.1027/1015-5759/a000644

ESM 1. Data management
ESM 2. Means, *SD*, and norms for UK and Ireland
ESM 3. Overall profile of norms (UK, 14–17)
ESM 4. Overall profile of norms (UK, 18–29)
ESM 5. Overall profile of norms (UK, < 3 0)
ESM 6. Histograms for distribution of personality scores
ESM 7. IPIP NEO scoring tool 1

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History

Received November 3, 2019
Revision received July 3, 2020
Accepted July 17, 2020
Published online August 12, 2021
EJPA Section / Category Personality

Open Data

Johnson's IPIP-NEO data repository is available at https://osf.io/tbmh5. We report how we determined our sample size, all data exclusions (if any), all data inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all measures in the study, and all analyses including all tested models. If we use inferential tests, we report exact *p* values, effect sizes, and 95% confidence or credible intervals.

Open Data: I confirm that there is sufficient information for an independent researcher to reproduce all of the reported results, including codebook if relevant (see ESM 1).

Open Materials: I confirm that there is sufficient information for an independent researcher to reproduce all of the reported methodology (see ESM 1).

Preregistration of Studies and Analysis Plans: This study was not preregistered.

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