Predicting Personality Test Scores with Machine Learning Methodology:

Investigation of a New Approach to Psychological Assessment

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Abstract

In principle, neural networks and other algorithms of machine learning can perfectly map unique relations of any complexity between input and output variables. We investigate whether using multi-layer neural networks allows improving personality assessments by constructing short-tests that are more efficient. Personality data for $N = 3,498$ participants from Germany, the US and the UK was collected using the *International Personality Item Pool-300-item-version* (IPIP-300 or IPIP-NEO), the *Big Five Inventory* (BFI-10) and the *HEXACO Personality Inventory-60* (HEXACO-PI-R). We trained 40 multi-layer neural networks on this data to predict individuals' scores on the Big-5-personality dimensions as well as facet scores from a 30-item version of the IPIP. A neural network based short-test version, IPIP30-NNet, predicted Big-5 dimensions from IPIP-300 as well as its facets with high accuracy. The correlations with the long-test scores (IPIP-300) were significantly higher compared to short-tests using a standard averaging algorithm and a multiple regression. Particularly for the facet scores, IPIP30-NNet lead to substantial improvements in predictive validity ($\Delta r = .04 - .17$). Additionally, as a syntheses of all three personality tests we calculated Big-5-“superscores”, which could be predicted from IPIP30-NNet with high accuracy as well. Our results demonstrate that neural network based diagnostic can be used to receive a very detailed individual personality profile based on very few information. We discuss challenges, potentials and future directions for using machine learning to improve standard psychological assessment.

Keywords: machine learning, neural networks, psychological assessment, personality, IPIP.

Predicting Personality Test Scores with Machine Learning Methodology:

Investigating a new Approach in Psychological Assessment

Big Data and *machine learning* have become increasingly important for the economic success of companies as well as everyday life of people. In psychological research, they receive increasing interest as well. Recent activities in this field have, for example, focused on the analysis of online behavior/digital footprints to predict “offline” behavior or in some cases personality. Since it has become comparably easy to document transactions on the internet in detail and on an individual level, it is now possible to accumulate very large datasets on individual human behavior. The extent and the complexity of these large datasets (key word: Big Data) have necessitated new forms of analyses that have emerged under the term machine learning. In the light of the recent replicability crisis in psychological research (Open Science Collaboration, 2015), Big Data is already regarded as a potential silver lining due to largely increased statistical power in most cases (Kosinski, Wang, Lakkaraju, & Leskovec, 2016).

Notable usage of machine learning has been demonstrated by Kosinski, Stillwell, and Graepel (2013): Based on data of several thousand participants they were able to predict, e.g. information on race, gender, age, sexual orientation and (considerably less accurate) personality and cognitive ability – only by referring to publicly available social media behavior. This has partly led to bizarre results, e.g. liking curly fries emerged as the best predictor for high intelligence and liking the movie “The Dark Knight” was the best predictor of having only few friends. Although findings like this have undeniably anecdotal qualities, they also highlight a major issue for data mining in psychology: the absence of a psychological theory. Most of the variables that are used to predict psychological variables might only have spurious relationships with their psychological counterparts. Bleidorn and Hodwood (2019) compared machine learning in psychology to the external (theory-free) scale construction of the *Minnesota Multiphasic Personality Inventory* (MMPI, Hathaway & Meehl, 1951).

In our study, we focused on a different implementation of machine learning techniques. We did not focus on non-psychological variables in order to predict psychological test scores. Instead, we used information from items from personality tests to predict sum scores for the global personality factors as well as personality facets. We aimed to test, whether machine-learning technology can be used to construct personality tests that are more efficient than previous test in that they provide more precise predictions from the same amount of data.

We apply multi-layer neural networks, a special form of machine learning technologies. Neural network are based on classic work in cognitive science on parallel distributed processing by spreading activation (Rumelhart, Hinton, & McClelland, 1986) and back-propagation learning (Rumelhart, Hinton, & Williams, 1986). They are used both as technology to solve recognition problems and to develop theories of human cognition. As methodology they are, for example, used to recognize handwritten letters (LeCun, Bottou, Bengio, & Haffner, 1998) or to predict sexual orientation from facial images better than humans (Wang & Kosinski, 2018). Variants of these networks have also been used to model many kinds of cognition (McClelland et al., 2010; McClelland, Mirman, Bolger, & Khaitan, 2014) including decision making (Glöckner & Betsch, 2008; Glöckner, Hilbig, & Jekel, 2014; Holyoak & Simon, 1999; Jekel, Glöckner, & Bröder, 2018; Thagard & Millgram, 1995).

In the current research, we investigate the potential of using neural networks to develop personality tests that are more efficient. We are fully aware of various limitations of our approach that should be explicated in advance. We can neither provide a full-fledged axiomatic system for a machine-learning based test theory nor can we test the full potential of the approach in this paper. We, however, try to provide a proof of concept and discuss advantages, challenges and some potential future directions (e.g., adaptive testing).

In our research, we follow a simple approach: Given that (with sufficient data) neural networks can map any relation of any complexity (Nielson, 2015), it could in principle be possible to predict personality traits from personality items better than with any other method.

For the application of neural networks, no assumptions concerning the functional form of the relation, independence of errors (such as in classical test theory) or local stochastic independence (such as in probabilistic test theory) are required. The network extracts the relation between the input and output variables. The success and the potential degree of overfitting is evaluated in an out-of-sample prediction, that is, a prediction for data that was not used for fitting the network (cross-validation). To train a neural network a criterion is required. Since true values of personality traits are not observable, in the current investigation we use the personality scores of a longer test (and later also the combination of multiple longer tests) as criterion that is used for learning and out-of-sample prediction.

In our investigation, we use answers to 30 items from the IPIP to predict sum-scored from the full version of the personality test. To measure the potential of neural networks for improving the efficiency of tests, we compare the predictive accuracy of a neural network based short-test (IPIP30-NNet) with the predictive accuracy of a standard short test (IPIP30-Stand) and a test based on multiple regression (IPIP30-Reg). The IPIP30-Stand uses the average of the respective scale items (taking into account reversals) as predictor. The regression based test IPIP30-Reg uses a linear regression to predict scale scores from all items belonging to the scale, hence allowing for a weighted average. Note that the IPIP30-NNet, IPIP30-Stand and IPIP30-Reg all comprised the same 30 items, but used different rationals to generate their respective overall test scores.

Furthermore, we investigate whether IPIP30-NNet can also predict personality more generally. Instead of validating the test against other tests, we utilize the feature of neural networks that they can be enhanced by improving the quality of their criterion. To do so, we calculate Big-5-“superscores” by combining the results from three personality measures:

International Personality Item Pool-300-item-version (IPIP-300), the *Big Five Inventory* (BFI-10) and the *HEXACO Personality Inventory-60* (HEXACO-PI-R) and train the network to predict these superscores. This approach would in principle allow developing tests that not only correlate with other tests (as in standard criterion validation procedures), but to merge the content of available operationalizations for the same personality construct into one single scale.

Method

Participants

We recruited an according to age and gender representative sample of 5,056 subjects from Germany, Great Britain and the United States using the online panel provider *Toluna*. We had to significantly reduce this sample since (a) for a subsample it was optional to answer every item and therefore we faced a substantial amount of missing values and (b) we implemented eight *attention control questions* and removed participants who answered at least one of those in an inattentive way. Our final study sample comprised $N = 3,498$ participants (50.1% female). To avoid fatigue, the questionnaire was split in three parts that were completed on separate days. Our main measure IPIP -300 was included in the first wave, while the other personality measures followed in the subsequent waves, which led to substantial drop out for the peripheral personality measures. Participation was rewarded by the panel provider.

Materials

We measured the Big 5 using three different tests: The most extensive measure was the 300-item *IPIP-NEO/IPIP-300* (Goldberg, 1999), a five-factor-test with 30 subfacets (six for each global factor) that mirrors the structure of the *NEO-Personality Inventory-Revised* by Costa and McCrae (2008) and is derived from the *International Personality Item Pool*. All participants of our final sample ($N = 3,498$) completed the IPIP-NEO in total. In our study the reliability of the global factors was very good (see Table 1). The internal consistencies for the

30 subfacets were good as well (average $\alpha = .81$) with *depression* as the most reliable one ($\alpha = .91$) and *liberalism* with the lowest reliability ($\alpha = .65$). We also used the 10-item *Big Five Inventory* (BFI-10; Rammstedt, Kemper, Klein, Beierlein, & Kovaleva, 2013) with only two items for each global factor. We had complete data for $n = 1,793$ participants. In our study the internal consistencies were unsurprisingly low, ranging from $\alpha = .31$ to $\alpha = .72$. Furthermore, the 60-item-version of the *HEXACO-Personality Inventory-Revised* (HEXACO-PI-R; Ashton & Lee, 2009) was used. In the underlying HEXACO-model there is an additional factor to the Big 5-space (*honesty-humility*) and some aspects of the five global factors are “rearranged” in the sense that some contents then appear in other factors. We had complete data for $n = 2,240$ participants. There were ten items per global factor and the internal consistencies ranged from $\alpha = .71$ to $\alpha = .80$. We used a likert-scale ranging from 1 to 5 for all instruments mentioned above.

The 30 items for the short-tests (IPIP30-NNet, IPIP30-Reg, IPIP30-Stand) were selected by including the items with the highest item-rest correlation for each of the 30 facets of the IPIP-NEO. The resulting 30 items are provided in the appendix. The internal consistencies regarding the global factors were comparably low: $\alpha = .44$ for Agreeableness, $\alpha = .54$ for Openness, $\alpha = .67$ for Conscientiousness, $\alpha = .68$ for Extraversion and $\alpha = .82$ for Neuroticism.

Superscores

We generated so-called “superscores” by aggregating the participants’ test scores from the three Big 5-test using the following formula:

$$\text{Superscore} = \frac{\alpha_{\text{IPIP}} * \text{IPIP-score} + \alpha_{\text{BFI10}} * \text{BFI10-score} + \alpha_{\text{HEXACO2}} * \text{HEXACO2-score}}{\alpha_{\text{IPIP}} + \alpha_{\text{BFI10}} + \alpha_{\text{HEXACO2}}}$$

$\alpha_{\text{IPIP/BFI10/HEXACO2}}$ is the coefficient for internal consistency of the respective personality factor scale. Note that the “HEXACO2-score” is the product of rearranging the six global factors into the original five factor structure. We reorganized the HEXACO-subcales and their items based on the descriptions by Ashton (2017) regarding the HEXACO-model: *honesty-humility* was completely merged with agreeableness while the *patience*-facet was removed from agreeableness and added to neuroticism. The IPIP/BFI10/HEXACO2-sum-scores were also additionally averaged by the number of items that they were based on (e.g., a BFI-10-sum-score was divided by 2 while an IPIP-sum-score was divided by 60).

Neural networks

Neural networks were used to predict the dimensions and the facets of the IPIP-NEO as well as the overall dimensions scores (superscores) from a short 30-item version of the same test. We used fully-connected feedforward networks with one input layer, two hidden layers and one output layer. The input layer consisted of 610 nodes, which represented the 300 item ratings (scale: 1 - 5, centered) and nodes for age, sex, and country dummies (Germany: yes = 1, no = 0, UK: yes = 1, no = 0, US: yes = 1, no = 0) (all centered). For each of the 305 variables a missing value indicator node was included, resulting in a total of 610 input nodes. Including missing value indicators allowed the network to be trained for any subset of items. The hidden layers contained of 100 nodes each and used a logistic choice function. The output layer contained of 50 nodes that represented to probability of the bins of the predicted variable (1 - 50) using a softmax-activation function. We improved the efficiency of the training by slightly perturbing the input by including the 30 items of the short-test (IPIP30-NNet) plus a random sample of 1% of the remaining items. To train the network we used back-propagation learning with a cross-entropy cost function and L2 weight regularization (Nielson, 2015) with mini-batches of size 20. We used a learning parameter $\eta = .5$ for the first 100 learning epochs and $\eta = .1$ for further 50 learning epochs.

The process of generating the superscores and the implementation of neural networks to predict both superscores and facet scores are depicted in Figure 1.

Results

Descriptive statistics and intercorrelations

Descriptive statistics for the study variables are depicted in Table 1. Note that the study sample for each of the Big 5-tests varied significantly.

The intercorrelations of the study variables are presented in Table 2. All three measures of the Big 5 showed convincing evidence for convergent and discriminant validity, since every global-factor-scale was at least strongly related (i.e. $r > .5$) to its respective match from the other tests.

Analysis of structure

We used *confirmatory factor analyses* regarding the IPIP-NEO to inspect if the presumed structure of the inventory was appropriate. We tested for one-dimensionality regarding each global factor. The results are depicted in Table 3. The results were not satisfactory for any global factors, therefore we could not assume that our items were adequate to measure a common, one-dimensional construct.

Superscores

The descriptive statistics of the five superscores are depicted in Table 4. Note that there was a small gain regarding reliability for the global factors compared to the IPIP-NEO. The superscores were highly correlated with their respective IPIP-NEO-counterpart.

Predictive validity

The fitting results and the predictive validity of the short-tests (IPIP30-NNet, IPIP30-Reg, and IPIP30-Stand) for the Big-5 factors and facets from the IPIP-NEO are depicted in Figure 2. Point predictions of the neural network were computed as average of the probability distribution for the possible scale values (split in 50 bins, each presented by the activation of

one output node). Of particular interest is the comparison of the validity for predicted values, which we focus on in the following.

Overall, the correlations for predictions of the neural network are very close to the reliabilities of the respective scales. For the most reliable IPIP-dimension neuroticism, for example, the network predictions correlated .94 with the criterion, which in itself had a reliability of .96. For the least reliable dimensions, openness and agreeableness, the predictive validity was .86 while the reliability of the long scales was .90. Similar results were observed for the IPIPNEO-facets: the predictive validity of the most and least reliable facets was close to the respective reliabilities of the facets (neuroticism-depression: predictive validity = .90, α = .91; openness-liberalism: predictive validity = .65, α = .65). Hence, with the available data we were able to train neural networks that predicted the criteria close to the theoretically possible maximum. We observe some degree of overfitting for the neural network in that the validities for fitted values were roughly $\Delta r = .03$ higher than for predicted values.

When comparing the predictive validity of the neural network based test and the other tests for the dimension, the neural network performed better than the regression ($b_{\Delta r} = -.01$, $t = 6.05$, $p < .001$), and the standard averaging procedure ($b_{\Delta r} = -.02$, $t = 10.97$, $p < .001$). Coefficients $b_{\Delta r}$ refer to the difference in predictive validity r with negative numbers indicating an advantage of the neural network. The advantage of the network is most pronounced for neuroticism but prevails for most of the dimensions. Overall, the advantage in predictive accuracy of the neural network for the Big-5 dimensions seems to be reliable but relatively small in magnitude.

For the facets, the advantages of the network in comparison to the standard test (that used the single item to predict the facet score) were more pronounced ranging from 4 to 17

validity points ($\Delta r = .04$ to $.17$; overall $b_{\Delta r} = -.091$, $t = 39.00$, $p < .001$).¹ The predictive validity of all tests was particularly low for the low reliable facets (i.e. openness-liberalism).

The fitting of the superscores revealed that the neural network was very well able to predict superscores as well (Figure 3) with predictive validities ranging from .80 (agreeableness, $\alpha = .92$) to .87 (neuroticism; $\alpha = .96$). The predictive validity for superscores correlated with the reliability but in contrast to the predictions for the IPIP-300 score reported above, validity remained considerably below reliability.

The neural network performed similar to the regression in predicting superscores ($b_{\Delta r} = -.0001$, $t = 0.05$, $p = .96$) but better than the standard test ($b_{\Delta r} = -.024$, $t = 6.79$, $p < .001$) (Figure 3). However, it should be noted that the fitting sample for the superscores was small ($N = 897$). It contained only roughly half of the overall sample that was used for fitting the IPIP-NEO dimension scores reported above. This might explain why machine learning was not able to use its full potential and predictions remained considerably below reliabilities.

Finally, when considering the absolute deviation of the predictions from the true values (regarding the IPIP-NEO global factors and its facets), regression performed slightly better than the neural network (Figure 4, top). Still, both showed acceptable values of an average absolute deviation of 4 - 6% from the criterion values. There seem to be tendencies to over- or underestimation of the networks in some of the facets, which might be solved by adapting the respective norm values. For the facets, the neural network (Figure 4, bottom) outperformed the standard test considerably also concerning absolute deviation.

The neural network is constructed to predict the probability distribution of all possible values, not only the point predictions that we considered so far. Typical prediction vector for six participants are depicted in Figure 5. Note, that the network does not require any assumptions concerning the functional form. For each bin, the probability is predicted

¹ Note, that the 30 items of the short test contained only one item per facet. Therefore, it was conceptually not meaningful to implement regression based-tests for facets.

separately, which can also capture (e.g.) multi-modal predictions. The interesting property of the network is that the probability of each single value as well as the confidence intervals can be directly read from the distribution. With sufficient data and when overfitting is avoided, the neural network will approximate the optimal integration of probability distribution according to a Bayesian optimal solution (cf. Fox, 2010).

Discussion

In previous work, Big Data and machine learning have mainly been used to predict personality from seemingly irrelevant other data (e.g., online traces) and succeeded surprisingly well with predictive validities of .29 to .43 (Kosinski et al., 2013). In the current analysis, we tested whether neural network can also be used to develop more efficient personality tests that provide detailed information with only few items. We find support for this assumption. With IPIP30-NNet, we developed an efficient 30-item short-test that predicts Big-5 personality (as measured by longer tests) with high precision of $r = .86$ to $.94$ and in several cases close to the theoretically possible maximum.

The advantages in predictive accuracy over a standard test (using unweighted item averaging) and a regression model (using weighted item averaging) was reliable but relatively small for the five dimensions (when predicting IPIP-300 scores). There was, however, a larger advantage in predicting the 30 Big-5 facets. Overall, IPIP30-NNet predicted facet scores close to the facet scales' reliabilities and considerably better than using the single items alone. Hence, combining neural networks with short tests, as we did in IPIP30-NNet, provides the possibility to measure personality more precisely and particularly in a more detailed manner.

When predicting Big-5dimension superscores, calculated as weighted averages over multiple personality tests, IPIP30-NNet performed good as well. However, predictive validity was considerably below scale reliability. The network did not predict better than a regression-based test (IPIP30-Reg), but better than a standard item averaging test (IPIP30-Stand). The less superior results concerning superscores might be due to the lower sample size for the

superscores. The additional personality tests were completed in later waves after the IPIP-300 leading to considerably drop out. Drop outs might have been systematically related to personality traits, which could potentially bias the network based estimation. Finally, the slightly different conceptualizations of Big-5 factors in the other tests might have played role, although we tried to correct for this by rearranging facets in the HEXACO-PI-R. Further research is needed to investigate these issues in detail.

The current work provides a proof of concept that neural networks can be usefully applied to improve personality assessment based on standard personality items. Predictions are generally of high accuracy and - in comparison to other tests - it is even possible to predict facets with a very short instrument. Implementation of such network-based tests is also practically possible on standard servers, since only the estimation procedure needs high calculation power.

Challenges and future directions

There are many open questions and challenges for future developments. Further analytical and empirical work is required to develop a full-fledged neural network based test theory. It has to be tested in more detail, whether not only the point-predictions used in the current study but also the predicted probability distributions are valid or need correction procedures (e.g., in the extremes or for overfitting).

As discussed in the introduction, the theory-free use of machine learning to predict psychological variables or specific behavior has been repeatedly criticized. We used item scores from a specific global factor to predict that overall factor scores, which is of course in line with standard theory. Additionally, IPIP-30-NNet also utilized every other IPIP-30-NNet-item for the prediction (e.g., an extraversion-item to predict neuroticism etc.). One might argue that this approach contradicts the Big-5-model and is somehow “theory-free” as well.

One promising direction for future work would be to apply neural networks also for adaptive testing. In principle, neural networks can be trained to work with any subset of items

and to select the most informative item given the current status of assessment. Specifically, to realize neural network based adaptive testing, meta-networks would need to be trained that are able to select the most informative of the remaining item (taking into account all to be predicted dimensions and facets simultaneously).

An interesting further perspective is the construction of “blended tests” that comprise of traditional psychological test items as well as non-psychological questions (e.g., regarding curly fries...) and further variables from objective tests (e.g., response times for each item, curvature of the mouse-movements). The non-psychological questions should be correlated with personality, but they should also have low face-validity (with regards to the respective personality dimension). Such blended tests would be harder to fake than standard tests and they would use available information in a most efficient manner. Machine learning techniques might not only be well-suited to identify such non-psychological and objective items.

Machine learning also allows using these items jointly with classic items in the measurement of personality. This could allow generating tests that would have a lower susceptibility to *faking*. Additionally, indicators for lying or non-serious responding could be (more) easily derived from neural networks. These possibilities still have to be explored in more detail.

Overall, the application of neural networks to optimize psychological assessment based on standard items seems to be a promising avenue for future research as well as practical applications of computer-based diagnostics.

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Appendix

#	question		dimension	facet	IPIP	facet	r_{facet}	α_{facet}
	question (german)	(english)			ID	code		
1	Ich vertraue anderen.	I trust others.	agreeableness	trust	4	A1	.69	.85
2	Ich benutze andere für meine eigenen Zwecke.	I use others for my own ends.	agreeableness	morality	99	A2	.62	.78
3	Ich liebe es, anderen zu helfen.	I love to help others.	agreeableness	altruism	74	A3	.59	.82
4	Ich mache oft kritische Bemerkungen über andere.	I have a sharp tongue.	agreeableness	cooperation	109	A4	.48	.68
5	Ich habe eine hohe Meinung von mir selbst.	I have a high opinion of myself.	agreeableness	modesty	204	A5	.61	.79
6	Ich empfinde Mitgefühl für jene, die es schlechter haben als ich.	I feel sympathy for those who are worse off than myself.	agreeableness	sympathy	59	A6	.53	.74
7	Ich erledige Aufgaben erfolgreich.	I complete tasks successfully.	conscientiousness	self-efficacy	5	C1	.61	.84
8	Ich hinterlasse Unordnung in meinem Zimmer.	I leave a mess in my room.	conscientiousness	orderliness	190	C2	.66	.84
9	Ich halte meine Versprechen.	I keep my promises.	conscientiousness	dutifulness	45	C3	.50	.76
10	Ich tue mehr als das, was von mir erwartet wird.	I do more than what's expected of me.	conscientiousness	achievement-striving	140	C4	.59	.82

11	Ich beginne mit Aufgaben sofort.	I start tasks right away.	conscientiousness	self-discipline	85	C5	.72	.88
12	Ich treffe überstürzte Entscheidungen.	I make rash decisions.	conscientiousness	cautiousness	150	C6	.68	.81
13	Ich fühle mich wohl unter Menschen.	I feel comfortable around people.	extraversion	friendliness	62	E1	.72	.88
14	Ich bevorzuge es, alleine zu sein.	I prefer to be alone.	extraversion	gregariousness	157	E2	.61	.86
15	Ich übernehme gerne Verantwortung.	I take charge.	extraversion	assertiveness	12	E3	.62	.82
16	Ich bin immer beschäftigt.	I am always busy.	extraversion	activity level	17	E4	.39	.64
17	Ich suche das Abenteuer.	I seek adventure.	extraversion	excitement-seeking	52	E5	.69	.83
18	Ich habe viel Spaß.	I have a lot of fun.	extraversion	cheerfulness	57	E6	.68	.83
19	Ich fühle mich schnell gestresst.	I get stressed out easily.	neuroticism	anxiety	91	N1	.69	.85
20	Ich bin leicht reizbar.	I get irritated easily.	neuroticism	anger	36	N2	.77	.9
21	Ich bin häufig niedergeschlagen.	I am often down in the dumps.	neuroticism	depression	71	N3	.79	.91
22	Ich bin schnell eingeschüchtert.	I am easily intimidated.	neuroticism	self-consciousness	16	N4	.64	.81
23	Ich esse oder trinke oft maßlos viel.	I go on binges.	neuroticism	immoderation	111	N5	.54	.75
24	Ich gerate leicht in Panik.	I panic easily.	neuroticism	vulnerability	26	N6	.68	.87

25	Ich habe eine lebhaftes Phantasie.	I have a vivid imagination.	openness for experience	imagination	3	O1	.62	.82
26	Ich mag keine Kunst.	I do not like art.	openness for experience	artistic interests	158	O2	.67	.79
27	Ich erlebe meine Gefühle intensiv.	I experience my emotions intensely.	openness for experience	emotionality	13	O3	.56	.73
28	Ich mag keine Veränderungen.	I dislike changes.	openness for experience	adventurousness	168	O4	.64	.81
29	Ich liebe es, anspruchsvolle Texte zu lesen.	I love to read challenging material.	openness for experience	intellect	53	O5	.61	.83
30	Ich glaube, dass wir hart gegen Verbrechen durchgreifen sollten.	I believe that we should be tough on crime.	openness for experience	liberalism	268	O6	.45	.65

Notes. r_{facet} = item-total correlation regarding the facet; α_{facet} = internal consistency of the IPIP-NEO-facet.

Figures

Figure 1. Process of generating the superscores, the item selection for the IPIP30-NNet and its utilization with neural networks.

Figure 2. Model comparisons concerning validity in predicting the dimensions (top) and the facets (bottom) of the 300-item IPIP from the 30-item-version. net_fit, net_pred - neural network (fitting for the estimation set, $N = 1848$ and out-of-sample prediction for the test set $N = 1848$). reg_fit, reg_pred - multiple regression (fitting for the estimation set and out-of-sample prediction), stand_fit, stand_pred – standard averaging of items (estimation set and prediction set). Results are averaged over five trials of model fitting using different estimation and test sets, se refers to the variation between model fitting trials.

Figure 3. Model comparisons concerning validity in predicting Big-5-superscores (reliability-weighted averages from multiple Big-5-tests) from the 30-item-version of the test. net_fit, net_pred - neural network (fitting for the estimation set, $N = 837$ and out-of-sample prediction for the test set $N = 837$). reg_fit, reg_pred - multiple regression (fitting for the estimation set and out-of-sample prediction), stand_fit, stand_pred – standard averaging of items (estimation set and prediction set). Results are averaged over five trials of model fitting using different estimation and test sets, *se* refers to the variation between model fitting trials.

Figure 4. Model comparisons concerning error (in absolute deviation in % of the scale range) in predicting the dimensions (top) and the facets (bottom) of the 300-item IPIP from the 30-item-version. net_pred - neural network (out-of-sample prediction for the test set $N = 897$), stand_pred – standard prediction from the single item of the facet. Results are averaged over five trials of model fitting using different estimation and test sets.

Figure 5. Examples for predicted probability distributions for neuroticism superscores based on IPIP30-NNet. Dashed lines are the point predictions, solid lines are the true values.

Tables

Table 1

Descriptive statistics of the study variables

	α	M	M_{adj}	SD	skewness	kurtosis	SE
age		49.43		16.44	-0.15	-1.05	.28
IPIP-NEO Neuroticism	.96	158.20	2.56	37.21	0.36	-0.09	.63
IPIP-NEO Extraversion	.94	181.83	2.99	31.15	-0.20	0.15	.53
IPIP-NEO Openness	.90	201.72	3.34	25.67	0.02	0.00	.43
IPIP-NEO Agreeableness	.90	218.10	3.67	23.75	-0.35	0.24	.40
IPIP-NEO Conscientiousness	.94	222.17	3.76	28.68	-0.11	-0.15	.48
BFI-10 Neuroticism	.72	5.47	2.73	2.01	0.29	-0.54	.05
BFI-10 Extraversion	.66	5.78	2.89	1.90	-0.01	-0.45	.04
BFI-10 Openness	.55	6.85	3.42	1.93	-0.18	-0.58	.05
BFI-10 Agreeableness	.31	6.61	3.30	1.62	-0.27	-0.12	.04
BFI-10 Conscientiousness	.48	7.61	3.80	1.60	-0.26	-0.44	.04
HEXACO Neuroticism	.80	31.47	2.99	6.72	-0.08	-0.02	.14
HEXACO Extraversion	.82	32.03	3.19	6.96	-0.34	-0.03	.15
HEXACO Openness	.77	32.40	3.25	7.21	-0.10	-0.44	.15
HEXACO Agreeableness	.76	32.25	3.45	5.92	-0.14	0.31	.13
HEXACO Conscientiousness	.75	37.23	3.74	5.60	-0.16	-0.13	.12
HEXACO Honesty-Humility	.71	37.14	-	6.24	-0.31	-0.07	.13

Notes. $N = 3498$ for the IPIP-NEO, $n = 2240$ for the HEXACO-PI-R, $n = 1793$ for the BFI-10.

The participants raw sum scores per global factor were additionally averaged by the number of items for each Big-5-test (IPIP-NEO, BFI-10, HEXACO-PI-R) to fit an overall score ranging from 1-5; these means are depicted under M_{adj} ($n = 1793$; for the HEXACO-PI-R the M_{adj} is based on the rearranged scores.) Every other descriptive statistics are based on M .

Table 2

Intercorrelations of the study variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 IPIP-NEO_N															
2 IPIP-NEO_E	-.474														
3 IPIP-NEO_O	-.094	.436													
4 IPIP-NEO_A	-.195	.098	.191												
5 IPIP-NEO_C	-.566	.313	.099	.285											
6 BFI-10_N	.741	-.396	-.058	-.043	-.308										
7 BFI-10_E	-.341	.708	.238	.021	.143	-.370									
8 BFI-10_O	-.075	.272	.606	.049	.068	-.076	.194								
9 BFI-10_A	-.255	.232	.145	.571	.141	-.176	.175	.061							
10 BFI-10_C	-.349	.269	.077	.226	.637	-.230	.191	.094	.154						
11 HEXACO_N	.578	-.141	.083	.225	-.159	.549	-.118	.019	.044	-.050					
12 HEXACO_E	-.649	.773	.267	.104	.370	-.536	.658	.197	.271	.294	-.271				
13 HEXACO_O	-.123	.302	.751	.100	.077	-.082	.173	.627	.102	.051	-.048	.257			
14 HEXACO_A	-.416	.184	.091	.567	.213	-.286	.110	.028	.578	.203	-.122	.260	.093		
15 HEXACO_C	-.311	.140	.086	.194	.750	-.123	.031	.107	.050	.536	-.081	.186	.114	.081	
16 HEXACO_HH	-.173	-.114	.005	.475	.205	-.051	-.102	.006	.166	.171	-.023	-.019	.009	.283	.244

Notes. $N = 3498$ for the IPIP-NEO, $n = 2240$ for the HEXACO-PI-R, $n = 1793$ for the BFI-10.

Table 3

Test for one-dimensionality regarding each global factor of the IPIP-NEO

Global factor	Goodness of fit indicators					
	χ^2	<i>df</i>	<i>p</i>	CFI	RMSEA	SRMR
Neuroticism	34513.501	1710	< 0.001	.682	.074	.069
Extraversion	41844.791	1710	< 0.001	.544	.082	.088
Openness	39063.212	1710	< 0.001	.433	.079	.087
Agreeableness	42236.182	1710	< 0.001	.415	.082	.105
Conscientiousness	41878.947	1710	< 0.001	.527	.082	.095

Notes. We did only test for one-dimensionality regarding each global factor and did not test possible higher-order-models involving the 30 IPIP-NEO-facets. *p* = p-values of the chi-square-tests, CFI = Comparative Fit Index, RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residual.

Table 4

Descriptive statistics for the “superscores”

	α	M	SD	skewness	kurtosis	SE	r_{IPIP}
Superscore Neuroticism	.96	2.75	0.64	0.26	-0.16	.02	.91
Superscore Extraversion	.95	3.02	0.62	-0.21	-0.13	.01	.91
Superscore Openness	.93	3.33	0.59	-0.05	-0.38	.01	.87
Superscore Agreeableness	.92	3.53	0.42	-0.32	0.34	.01	.89
Superscore Conscientiousness	.95	3.76	0.49	-0.2	-0.12	.01	.92

Notes. $N = 1793$, Superscores were only calculated if test scores were available for all three Big 5-tests (IPIP, BFI-10, HEXACO) and were based on the respective raw score adjusted by item number (possible range 1-5). r_{IPIP} = correlation with the respective IPIP-NEO-global factor.