# What makes a Computer Wiz?

## Linking Personality Traits and Programming Aptitude

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## Abstract

Computer applications have become indispensable work tools in most organizations. As a consequence, software engineering abilities are desired skills for many employees. Therefore, the study explored individual differences predicting programming aptitude. A meta-analysis on 19 independent samples (total $N$ = 1,695) highlighted that programming aptitude was associated with three personality traits, conscientiousness, openness, and introversion. Moreover, the three traits explained incremental variance components beyond general mental abilities. In contrast to stereotypical beliefs, programming aptitudes were not associated with socially undesirable traits such as disagreeableness or neuroticism.


*Keywords*: computer, programming, software engineering, Big Five, mental ability

What makes a Computer Wiz?

Linking Personality Traits and Programming Aptitude

Modern technologies profoundly shape people's lives and altered, for example, how people communicate with each other, share and retrieve information, or spend their leisure time (e.g., Jadin, Gnambs, & Batinic, 2013). Frequently, developers of such applications are attributed with various rather unfavorable characteristics; for example, prevalent stereotypes describe software engineers as socially inept introverts that are single-mindedly focused on computers (e.g., Cheryan, Plaut, Handron, & Hudson, 2013). However, in recent years the profession has undergone a fundamental change in public perception. Many computer programmers transformed into desirable role models with prestige for many adolescents and adults. Programmers such as Linus Torvalds, the originator of Linux, or Steve Wozniak, the software designer of Apple computers, became individuals many people strive to emulate. Among others, this is attributed to the continuing growth in employment opportunities and increased salaries in the computer industry (Freedman, 2011). Thus, it seems important to more closely examine the psychological profile of these individuals. In contrast to previous research that primarily focused on motivational and attitudinal attributes of computer programmers (e.g., Hertel, Niedner, & Hermann, 2003) the present study examined stable individual differences and presents a meta-analysis on personality traits that contribute to programming aptitude.

## Predictors of Programming Aptitude

Individual differences can be distinguished into two components that either refer to peoples' typical performance or maximal performance (cf. DeYoung, 2011). Typical performance describes how people generally behave in a given situation. It can be distinguished based on five basic dimensions of personality, openness to experiences, conscientiousness, extraversion, agreeableness, and neuroticism. These Big Five of personality have been shown to predict a variety of real-life behaviors including, among others, academic performance (McAbee & Oswald, 2014) and various work-place behaviors (Salgado & Táuriz, 2014). Two personality traits might be expected to be particularly relevant for programming aptitude. First, conscientiousness characterizes people that are thorough, careful, and detail-oriented. These attributes seem particularly important for software engineering because coding requires programmers to also focus on minor details (i.e. minor typographic errors in the computer code can completely break a software application).

*H1: Conscientiousness is positively associated with programming aptitude.*

Creating new software applications also requires the generation of new algorithms and the development of new software architectures. Therefore, programmers require the ability to think in unconventional ways and derive new working solutions for a problem at hand. Since imagination, creativity, and intellectual curiosity are central components of trait openness (McCrae & Greenberg, 2014), it is expected that programming abilities is also related to higher levels of openness.

*H2: Openness to experiences is positively associated with programming aptitude.*

Traditional stereotypes on computer geeks would suggest that programmers are somewhat socially incompetent loners that might also exhibit various psychological deficiencies (Cheryan et al., 2013). Along this line, it could be speculated that programming aptitude would also be associated with introversion, disagreeableness, and neuroticism. However, these preconceptions do not necessarily have an empirical basis. So far, there are no compelling reasons why socially undesirable traits should favor programming abilities. Indeed, previous meta-analyses identified near zero correlations between agreeableness and intelligence (Ackerman & Heggestadt, 1997). Results with regards to job performance are somewhat inconsistent and range for extraversion from zero to small positive correlations (Salgado & Táuriz, 2014). Therefore, no associations between these traits and programming aptitude are put forward.

In contrast to personality traits that reflect typical performance of individuals, cognitive competencies determine the amount of maximum performance individuals might theoretically demonstrate in a given situation (DeYoung, 2011). Numerous studies on job performance highlighted that general mental abilities are among the most important predictors of future success at the workplace (e.g., Kuncel & Heclett, 2010). Therefore, it is also plausible that programmers with better mental abilities are likely to produce superior software solutions and less error-prone code.

*H3: General mental abilities are positively associated with programming aptitude.*

These hypotheses are examined in a meta-analysis on programming aptitude. A structured literature search identified empirical research findings on personality traits and mental abilities that might predict proficiency in computer programming and combined these results in a statistical generalization. In contrast to single-sample studies, meta-analyses have the advantage of arriving at effect estimates that are not distorted by sampling error.

## Method

### Date Source

Relevant primary studies reporting on predictors of programming abilities were identified using a structured literature search in several bibliographic databases (ACM Digital Library, IEEE Xplore, PsycINFO, ProQuest Dissertations & Thesis Database, Google Scholar) using the keywords *programming*, *software engineering*, or *software development* in combination with *personality*, *Big Five*, *Five Factor Model or intelligence*. After reviewing the abstracts of the retrieved publications studies were included in the meta-analysis if they met the following criteria: (a) The study administered a validated personality scale that could be classified into the five factor framework. For instruments that were not constructed according to the Big Five model (e.g., Sixteen Personality Factors Questionnaire) scales were classified into the five personality dimensions using established taxonomies (cf. Gnambs, 2014). (b) Programming abilities were quantified using an objective performance test (e.g., number of errors in the program code); subjective evaluations of individual's coding proficiency were not included. (c) The study reported a relevant effect size (i.e. correlation). This literature search identified 19 publications that met the specified inclusion criteria. From these publications the following correlations were extracted that served as focal effects sizes for this study: (a) correlations between personality (i.e. the Big Five) and programming aptitude, and (b) correlations between general mental abilities (e.g., intelligence test performance, grade point average) and programming aptitude.

**Meta-Analytic Procedure**

The random effects meta-analysis was conducted with the *metaSEM* software in *R* (Cheung, 2014). To account for sampling error, each effect size was weighted by the inverse of its variance. Because some samples reported multiple correlation coefficients (e.g., using different measures of programming ability), these dependencies were acknowledged by parameterizing the meta-analysis as a multilevel model where individual effects are nested within samples. To examine the incremental effects of personality over general mental abilities these univariate meta-analyses were extended to a meta-analytical structural equation model (MASEM; cf. Bergh et al., 2014; Gnambs, 2013). MASEM involves two steps: First, a meta-analytical correlation matrix for the Big Five of personality, general mental abilities, and programming proficiency was constructed from several univariate meta-analyses (see Table 1). Meta-analytic correlations involving programming proficiency were derived in this study, whereas correlations between personality and general mental abilities were substituted from previous meta-analyses (Ackerman & Heggestad, 1997; Gnambs, 2013). Second, this correlation matrix was subjected to a conventional structural equation analysis using a maximum likelihood estimator. This analysis specified a simple multiple regression model; that is, programming proficiency was regressed on the five personality traits and general mental abilities. In line with prevalent recommendations (Bergh et al., 2014), this analysis used the harmonic mean sample size of each meta-analysis as sample size for the calculation of the parameters' standard errors (and consequently the significance tests). Because the evaluated regression model is just-identified typical goodness-of-fit indices are not reported.

## Results

The meta-analyses included 19 independent samples with a total of 1,695 participants. The mean percentage of female participants in these samples was 27% (*SD* = 10) and the mean age was 20 years (*SD* = 1.13). The samples originated from the United States (7), Australia (6), England (5), and Canada (1).

### Univariate Meta-Analyses

The results of the six meta-analyses on the relationship between programming aptitude, personality, and general mental abilities are summarized in Figure 1. The strongest predictor of programming aptitude were general mental abilities, $\rho = .29$, $z = 4.71$, $p < .001$; more competent programmers created significantly better software code with less errors. With regard to the five personality characteristics, the most important trait was openness, $\rho = .16$, $z = 7.60$, $p < .001$. In support of hypothesis 2, intellectual curiosity and creativity which are central components of the openness trait contributed to successful programming achievements. Moreover, also hypothesis 1 with regard to conscientiousness was supported, $\rho = .09$, $z = 2.11$, $p = .04$; more conscientious programmers were less error prone. Finally, also extraversion contributed to programming aptitude, $\rho = -.11$, $z = .2.75$, $p = .001$. Successful programmers exhibited more introverted personality traits. The two remaining Big Five traits, agreeableness and neuroticism, were not associated with programming aptitude, $\rho = .03$, $z = 1.34$, $p = .18$, and $\rho = -.02$, $z = -1.21$, $p = .22$, respectively. Overall, these results support hypotheses 1 to 3 indicating that successful programmers are characterized by increased general mental abilities, conscientiousness, and openness. In contrast, there is no evidence of pronounced undesirable trait characteristics (i.e. disagreeableness or neuroticism) for computer programmers.

### Meta-Analytical Structural Equation Analysis

Because the five traits of personality are typically correlated (cf. Gnambs, 2013), the unique effects of each trait on programming aptitude were examined using meta-analytical structural equation modeling (Bergh et al., 2014). To this end a meta-analytical correlation matrix (see Table 1) was subjected to a multiple regression analysis that included general mental abilities and the five personality traits as predictors of programming aptitude. These analyses replicated the results of the six univariate meta-analyses. Programming aptitude was best predicted by general mental abilities, $\beta = .28$, $p <. 001$. Moreover, openness, $\beta = .09$, $p <. 001$, conscientiousness, $\beta = .10$, $p <. 001$, and extraversion, $\beta = -.16$, $p < .001$, explained incremental variance components in programming aptitude beyond cognitive factors (see Table 1). Personality traits and general mental abilities jointly explained about 12 percent of variance in programming proficiencies.

## Sensitivity Analyses

The publications included in the present meta-analyses spanned over four decades (from 1974 to 2014). In order to determine the stability of the previously presented results, meta-regression analyses were conducted to examine whether the relationships between programming proficiency, personality, and mental abilities changed over time. Thus, each univariate meta-analysis (see above) was extended to a regression model that included the publication year as a moderator. These analyses identified significant time trends for two traits: Openness predicted programming proficiency stronger in later years (predicted $\rho = .17$ in 2010) than in older studies (predicted $\rho = .06$ in 1990), $B = .01$, $SE = 00$, $z = 1.98$, $p = .048$; in contrast conscientiousness predicted programming proficiency weaker in newer studies (predicted $\rho = .05$ in 2010) than in earlier years (predicted $\rho = .17$ in 1990), $B = -.01$, $SE = 00$, $z = -2.32$, $p = .02$. For the remaining traits no moderating effects emerged, all $p$s > .05 (see Table S1 of the online supplement).

## Publication Bias

To determine whether a publication bias might have distorted the accuracy of the six meta-analyses, the distributions of their correlations were examined in more detail. PET-PEESE tests for funnel plot asymmetry (Stanley & Doucouliagos, 2014) conducted for each meta-analysis identified no significant association between the correlations and their standard errors (PET) or variances (PEESE), thus, providing no sign of publication bias, all *p*s > .10 (see Table S2 of the online supplement). Moreover, the corrected meta-analytic estimates of the PET-PEESE analyses showed robust effects for openness, $\rho_c = .17$, conscientiousness, $\rho_c = .11$, agreeableness, $\rho_c = .05$, and neuroticism, $\rho_c = -.05$. For general mental abilities, the corrected estimates indicated a slightly larger effect, $\rho_c = .59$, whereas no effect emerged for extraversion, $\rho_c = .02$. However, with less than 20 samples the respective estimates might be biased to some degree (Stanley & Doucouliagos, 2014).

## Discussion

Modern computer applications such as Facebook, Twitter or WhatsApp profoundly changed how people communicate and interact with each other. This led programming aptitudes to become a much sought after skill in recent decades and changed the view of software engineers in public perception. In contrast to some unfavorable stereotypical views (cf. Cheryan et al., 2013) software programmers became admired role models for many people. Therefore, the present study examined the psychological attributes that contribute to successful programming skills. The meta-analytic review identified four central factors. In line with previous research on job performance (Kuncel & Heclett, 2010), general mental abilities were the most important predictor of programming aptitude. However, personality traits describing how people typically behave exhibited additional effects. In line with the postulated hypothesis, conscientiousness and openness predicted programming skills, even after controlling for general mental abilities. However, the importance of the two traits for programming tasks seemed to change over the years. Whereas openness gained greater relevance in recent years, the importance of conscientiousness seemed to decrease.

Unexpectedly, the most important personality predictor was introversion. Introverts are reserved individuals with low levels of sociability; they tend to focus on their inner self instead of their social surrounding. Following Eysenck's (1967) neurobiological personality theory it might be speculated that introverts require little environmental stimulation to reach an optimal arousal. As a consequence, they might be more apt at software development tasks which require thoughtful analyses of design concepts and algorithms. In contrast, extraverted individuals might exhibit under-arousal during programming tasks because of their stronger need of social interactions (Charlton & Birkett, 1999). Thus, the reason why the software field is dominated by rather introverted individuals might be simply due to the fact that introversion benefits programming tasks.

A major strength of the presented results is that they are based on aggregated data from various primary studies. Thus, the meta-analysis was able to derive true effects corrected for sampling error. However, because the study relied on published results it was not possible to examine differential effects of more specific personality traits such as, for example, the need for cognition (Cacioppo & Petty, 1982) or the need for affect (Appel, Gnambs, & Maio, 2012). Thus, future research is encouraged to extend the presented results with more fine-grained measures of personality and mental abilities.

In conclusion, the presented meta-analyses identified a unique combination of stable individual differences that characterize successful computer programmers: general mental abilities, conscientiousness, openness, and introversion.

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[*] Articles included in the meta-analysis are listed in the online supplement.

Table 1.

*Meta-Analytical Regression of Programming Aptitude on Personality and Mental Abilities*

| | | | Regression analysis | | | Meta-analytic correlations | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | β | *z* | *p* | 1. | 2. | 3. | 4. | 5. | 6. | 7. |
| Criterion: | 1. | Programming aptitude | | | | 1.00 | | | | | | |
| Predictors: | 2. | Openness | 0.09 | 3.83 | < .001 | **.16** | 1.00 | | | | | |
| | 3. | Conscientiousness | 0.10 | 4.26 | < .001 | **.09** | *.03* | 1.00 | | | | |
| | 4. | Extraversion | -0.16 | -6.90 | < .001 | **-.11** | *.20* | *.11* | 1.00 | | | |
| | 5. | Agreeableness | 0.02 | 1.02 | .31 | **.03** | *.12* | *.22* | *.17* | 1.00 | | |
| | 6. | Neuroticism | 0.02 | 0.83 | .41 | **-.02** | *-.11* | *-.25* | *-.25* | *-.24* | 1.00 | |
| | 7. | General mental ability | 0.28 | 11.62 | < .001 | **.29** | *.33* | *.02* | *.08* | *.01* | *-.15* | 1.00 |

*Note*. Multiple $R^2$ = .12. Correlations in bold were derived in the present study. Correlations in italic were substituted from previous meta-analyses (Ackerman & Heggestad, 1997; Gnambs, 2013).

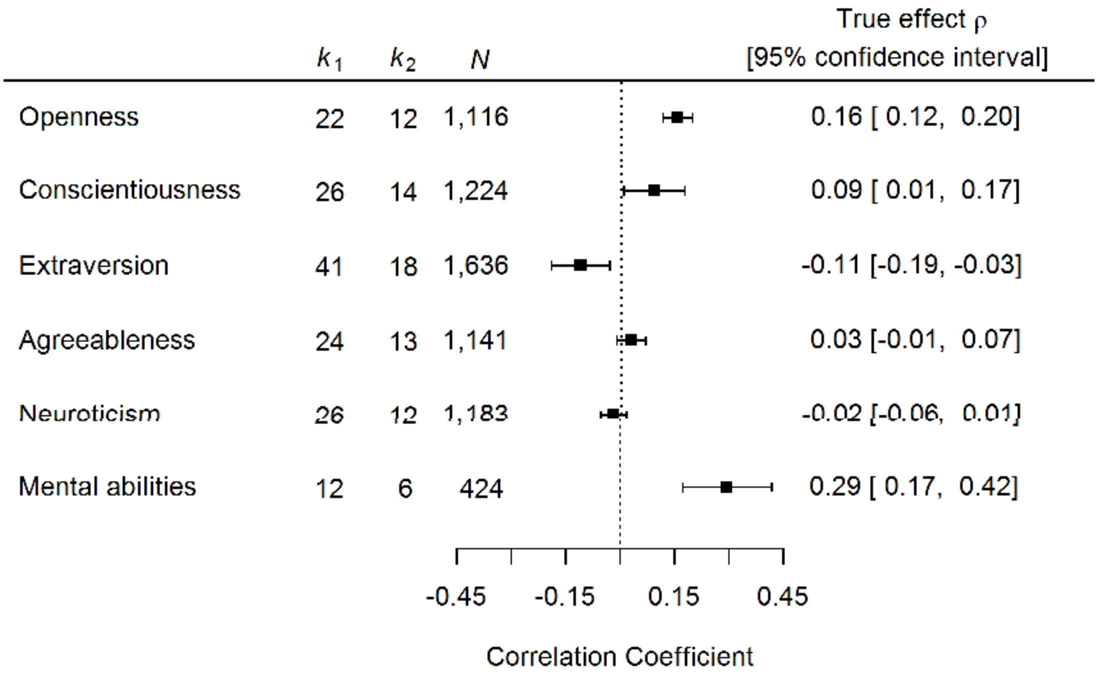


*Figure 1*. Forest plot for meta-analyses on programming aptitude. $k_1$ = number of effects, $k_2$ = number of samples.

Online Supplement for

„What makes a Computer Wiz?

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**Supplemental A: Tables**

Table S1.

*Meta-Regression Analyses for Publication Year as Moderator*

| | Openness | | | | Conscientiousness | | | | Extraversion | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\hat{\rho}$ | *B* | (*SE*) | *z* | $\hat{\rho}$ | *B* | (*SE*) | *z* | $\hat{\rho}$ | *B* | (*SE*) | *z* |
| 1. Intercept | | .19* | (.03) | 7.27 | | .03 | (.05) | 0.54 | | -.08 | (.06) | -1.40 |
| 2. Publication year | | .01* | (.00) | 1.98 | | -.01* | (.00) | -2.32 | | .02 | (.00) | 0.67 |
| 1990 | .06 | | | | .17 | | | | -.13 | | | |
| 2010 | .17 | | | | .05 | | | | -.09 | | | |
| Random variance | | .00[a] | | | | .01 | | | | .02 | | |
| $k_1$ / $k_2$ | | 22 / 12 | | | | 26 / 14 | | | | 41 / 18 | | |

| | Agreeableness | | | | Neuroticism | | | | Mental abilities | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\hat{\rho}$ | *B* | (*SE*) | *z* | $\hat{\rho}$ | *B* | (*SE*) | *z* | $\hat{\rho}$ | *B* | (*SE*) | *z* |
| 1. Intercept | | .03 | (.03) | 1.20 | | -.03 | (.03) | -1.06 | | .33 | (.22) | 1.49 |
| 2. Publication year | | .00 | (.00) | 0.22 | | .00 | (.00) | -0.52 | | .00 | (.01) | 0.16 |
| 1990 | .02 | | | | -.01 | | | | .31 | | | |
| 2010 | .03 | | | | -.03 | | | | .32 | | | |
| Random variance | | .00[a] | | | | .00 | | | | .02 | | |
| $k_1$ / $k_2$ | | 24 / 13 | | | | 26 / 12 | | | | | | |

*Note*. $\hat{\rho}$ =Predicted effect; $k_1$ = Number of effect sizes; $k_2$ = Number of samples. Because the publication year was recorded as deviation from 2014, the intercept represents the correlation in the year 2014. [a] Fixed parameter

Table S2.

*Meta-Regression Analyses for Publication Bias following the PET-PEESE Approach (Stanley & Doucouliagos, 2014)*

| | PET | | | | | | PEESE | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $B_0$ (*SE*) | *t* | $B_1$ (*SE*) | *t* | $B_2$ (*SE*) | *t* | $B_0$ (*SE*) | *t* | $B_1$ (*SE*) | *t* | $B_2$ (*SE*) | *t* |
| Openness | 0.19* (0.08) | 2.48 | -0.47 (0.81) | -0.58 | 0.00 (0.00) | 2.02 | **0.17*** (0.04) | 4.28 | -2.16 (3.79) | -0.57 | 0.00 (0.00) | 2.06 |
| Conscientiousness | **0.11** (0.13) | 0.83 | 0.00 (1.32) | 0.00 | -0.01* (0.00) | -2.43 | 0.13 (0.07) | 1.79 | -1.40 (6.21) | -0.23 | -0.01* (0.00) | -2.56 |
| Extraversion | **0.02** (0.07) | 0.21 | -0.98 (0.76) | -1.28 | 0.00 (0.00) | 1.94 | -0.04 (0.04) | -0.92 | -4.16 (3.44) | -1.21 | 0.00 (0.01) | 1.88 |
| Agreeableness | **0.05** (0.09) | 0.62 | -0.28 (0.84) | -0.33 | 0.00 (0.00) | 0.08 | 0.04 (0.04) | 0.93 | -1.29 (3.63) | -0.36 | 0.00 (0.00) | 0.07 |
| Neuroticism | **-0.05** (0.06) | -0.78 | 0.32 (0.70) | 0.45 | 0.00 (0.00) | -0.40 | -0.02 (0.03) | -0.72 | 0.15 (3.21) | 0.05 | 0.00 (0.00) | -0.33 |
| Mental abilities | **0.59** (0.30) | 1.98 | -3.00 (2.82) | -1.06 | -0.01 (0.01) | -0.97 | 0.40* (0.14) | 2.91 | -10.41 (10.85) | -0.96 | -0.01 (0.01) | -0.88 |

*Note*. $B_0$ = Intercept (i.e., the corrected estimate of the overall effect); $B_1$ = Regression weight for the standard error (PET) or the variance (PEESE) of the individual effect (i.e., the test for funnel plot asymmetry); $B_2$ = Regression weight for the publication year. PET-PEESE estimates of the overall effects are in bold.

* $p < .05$

**Supplement B: Articles included in the Meta-Analysis**

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