1 Do personality sex differences mirror personality differences across occupations?

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Abstract

It has been argued that the sex segregation of the labor market reflects personality sex differences. So far, few studies have used actual occupational titles. This study aims to tackle these limitations as well as to expand previous research by operationalizing occupations as occupational field (i.e. STEM vs. Non-STEM) and as occupational orientation (i.e. Prediger's people-things dimension). We replicated our analyses in three independent samples (Estonia, China, and UK) and, although there was no evidence that personality sex differences mirrored personality differences between occupational fields or between occupational orientations, results suggested that personality could be more relevant when choosing occupational orientation rather than occupational field.

Keywords: personality, nuances, sex, STEM, people-things

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Introduction

Sex differences in occupational preferences

Sex differences in occupational aspirations have been found to be stable from an early age. For instance, girls in primary and secondary school tend to prefer subjects like literature or history, whilst boys like those related to Science, Technology, Engineering, and Mathematics, *STEM* (Croll, 2008; Dekhtyar, Weber, Helgertz, & Herlitz, 2018; Gore et al., 2017; Gore, Holmes, Smith, Southgate, & Albright, 2015; Holmes, Gore, Smith, & Lloyd, 2018; Howard et al., 2011; Lubinski & Benbow, 1992; Su, Rounds, & Armstrong, 2009). Biology related fields like Medicine seem to also be preferred by girls. Some fields like art, law, and music seem to be gender-neutral (Howard et al., 2011). Ellis, Ratnasingam, and Wheeler (2012) used a sample with a wider age range (from 18 to 56) and found consistent small-to-moderate sex differences on specific jobs, women preferring beautician ($d=-.42$), daycare provider ($d=-.40$), and nurse ($d=-.30$) while men preferred being an athlete ($d=.37$), auto-mechanic ($d=.34$), test pilot ($d=.32$), or a police officer ($d=.24$). Richard A. Lippa has published several works showing that men and women incline towards different specific types of jobs and, although the effect sizes vary across countries, the results' patterns are similar (Lippa, 2005, 2008, 2010, 2020).

Recently, Stewart-Williams and Halsey (2021) published a comprehensive summary on sex differences in occupational aspirations and the uneven sex division across occupational fields – e.g.: men working in STEM while women work in non-STEM occupations. Stewart-Williams and Halsey (2021) conclusions suggested that occupational choices are influenced by stable personal characteristics. Although this is a recent paper, this hypothesis is not new. For instance, the relationship between personality and occupation has been of great interest for almost a century Holland (1959).

Several pieces of research have found women scoring higher in Extraversion, Agreeableness, and Neuroticism at the domain level (Paul T. Costa, Terracciano, & McCrae, 2001; Heineck, 2011; Kajonius & Mac Giolla, 2017; Lippa, 2005, 2008, 2010; Mac Giolla & Kajonius, 2019; Schmitt, Realo, Voracek, & Allik, 2008). Sex-differences in Conscientiousness and Openness to experience at the domain level are still less clear. Some studies suggest describing sex-differences in personality at the domain level might obscure differences at lower levels of aggregation like nuances or facets (Booth & Irwing, 2011; Del Giudice, Booth, & Irwing, 2012; Kaiser, 2019; Mac Giolla & Kajonius, 2019; Murphy, Fisher, & Robie, 2020). Nuances roughly correspond to single items and are the building blocks of facets which, in turn, make up domains (Robert R. McCrae, 2015). Hence, by studying nuances or facets we might, for instance, explain the contradictory results regarding sex differences in Openness (Booth & Irwing, 2011; Paul T. Costa, Terracciano, & McCrae, 2001; Feingold, 1994).

It has been argued that sex-differences in personality could make women better suited for specific jobs – e.g.: higher Agreeableness might be related with less female representation in solitary jobs like in math intensive fields (Hunalp, 2020). However, little research has focused on personality differences at domain level across actual occupations. This study aims to tackle this limitation. Based on the ideas put forward by Stewart-Williams and Halsey (2021), we hypothesize that if woman’s unequal representation across occupation categories (e.g.: STEM vs. Non-STEM) was partly explained by enduring personal characteristics like personality traits, then the personality differences across fields should mirror personality sex-differences. This and similar studies could have the potential of explaining uneven sex-representation across fields (Ceci, Ginther, Kahn, & Williams, 2014), improving vocational counseling, and enhancing job stability by better matching individuals to specific positions (Lubinski, 2000; Wilk, Desmarais, & Sackett, 1995).

Holland's RIASEC

As previously discussed, the relationship between occupations and personality traits has been thoroughly studied, but actual occupational titles have rarely been used. Research on personality traits and occupations has been mostly based on Holland's personality-environment typology, which establishes a link between people's *interests* and occupations or *environments*. Holland created interests measures so they mirrored "personality inventories which reveal information such as the person's values, attitudes, needs, self-concept, preferred activities, and sources of threat and dissatisfaction" (Holland, 1959, p. 36). Holland's model includes six categories (i.e. realistic, investigative, artistic, social, enterprising, and conventional – RIASEC), which have been used to describe both occupation's and people's characteristics.

Larson, Rottinghaus, and Borgen (2002) and Mount, Barrick, Scullen, and Rounds (2005) metaanalyses argue that personality domains and RIASEC categories must be different constructs, for none of the former explained more than 34% of the latter's variance. Other studies make similar claims on the basis that RIASEC categories are more stable during childhood and young adulthood than personality traits (e.g.: Hoff, Song, Einarsdóttir, Briley, & Rounds, 2020; Low, Yoon, Roberts, & Rounds, 2005). However, Holland himself defined RIASEC categories as personality inventories and research has shown a certain overlap between the two. Given that the relationship between personality and RIASEC categories is likely to be confounded, it might be redundant to study personality differences across occupations when this are coded into RIASEC categories. Therefore, research aiming to tackle the relationship between personality and occupations should focus in using actual occupational titles.

People vs. Things

Prediger (1982) found that RIASEC categories could be factor-analyzed into two by-polar dimensions representing occupational orientation: people-things and data-ideas.

The latter dimension informs about jobs that rely on pre-existing information as opposed to creating and developing new concepts. The people-things dimension reflects the degree to which socializing (e.g.: working with or directing teams, meeting clients, etc) is more relevant than working with objects or machinery. People-oriented jobs are related to Holland's enterprising, social and artistic occupations; while things-oriented jobs are closer to conventional, realistic, and investigative occupations.

Subsequent research showed that, unlike the data-ideas dimension, people-things occupational orientation correlated strongly with sex. Research has shown that women gravitate around people-oriented occupations and men towards things-oriented occupations (Hustad, Bandholtz, Herlitz, & Dekhtyar, 2020; Lippa, 1998; Su, Rounds, & Armstrong, 2009). Lippa (1998) found that the effect sizes for sex differences in the people-things orientation across three of his studies were higher than 1.20. This is among the largest sex-difference effect sizes ever found (Lubinski, 2000) but it might be inflated due to the aggregation of RIASEC scales which already present large sex differences. In a recent meta-analysis, Hoff, Briley, Wee, and Rounds (2018) showed that sex differences in people-things dimensions widen during secondary school, precisely when students make relevant choices about their educational fields. However, this gap narrows across adulthood, when women become more attracted to things-oriented occupations and men increase their preference for people-oriented occupations (Hoff, Briley, Wee, & Rounds, 2018). Still, Lippa, Preston, and Penner (2014) argued that, in developed countries, sex segregation between people- and things-oriented occupations is larger than across occupational status. Recently, Luoto (2020) showed that this tendency is even present in scientific publishing, where more women publish in people-oriented fields and more men in things-oriented fields. Altogether, these research findings suggest that occupational orientation (i.e. Prediger's people-things dimension) is an important predictor of sex differences in the labor market.

Occupational field vs. Occupational orientation

The unequal sex-representation in people vs. things occupations, as well as in STEM vs. non-STEM positions, lead many researchers to hypothesize that the STEM vs. non-STEM divide mirrors the people-things dimension (e.g.: Lippa, Preston, & Penner, 2014; Stewart-Williams & Halsey, 2021). To our knowledge, few studies have tested this hypothesis directly. Hence, we can only rely on the indirect information that some studies provide.

For instance, Hustad, Bandholtz, Herlitz, and Dekhtyar (2020) reported that people-oriented occupations correlate strongly with verbal demands ($r=.86$) and weakly with mathematical-demands ($r=-.16$). Given that, from a young age, women tend to outperform men in verbal tasks (Benbow, Lubinski, Shea, & Eftekhari-Sanjani, 2000; Stoet & Geary, 2013, 2018) and that there is a strong link between abilities and interests, their results suggested that women are more suited to people-oriented occupations. Moreover, this could mean that there is a latent factor like cognitive abilities contributing to the sex divide in both occupational field and orientation.

However, Hustad, Bandholtz, Herlitz, and Dekhtyar (2020) also found that things-oriented occupations were strongly negatively related to verbal-demands ($r=-.82$), but did not significantly correlate to mathematical-demands. Hence, mathematically demanding occupations were compatible with both, things and people-oriented occupations. Additionally, Lippa, Preston, and Penner (2014) asked 78 college students to rate the orientation of 60 occupations and found that certain occupations, especially those related to biology, were fairly distributed across the people-things spectrum. Together, these two studies suggests that people- or things-oriented occupations might be found within the same occupational field. In other words, it is possible that the occupational orientation dimension is nested within the STEM vs. Non-STEM divide.

Evidence on personality differences between actual educational and occupational careers

Few studies have compared personality across actual educational or occupational fields. Summarizing their results is not an easy task, for there is neither convergence in the personality inventories, nor on the operationalization of university studies or the occupational fields being used (De Fruyt & Mervielde, 1996; Vedel, 2016). As with occupations, some studies use bachelor titles (e.g.: Clariana, 2017) but others recategorize them into RIASEC (e.g.: Kaufman, Pumacahua, & Holt, 2013). Results also vary depending on which fields are included and compared – e.g.: social sciences students in De Fruyt and Mervielde (1996) scored the highest in openness but they might have scored lower than arts students had they been considered like in Kline and Lapham (1992).

Recently Vedel (2016) did a literature review on personality differences across university degrees. They found medium effect sizes in Extraversion, with students in Economics, Law, Political Sciences, and Medicine scoring higher than those in Arts, Humanities and Sciences. On the other hand, Natural Sciences tend to score higher in Agreeableness (De Fruyt & Mervielde, 1996; Rubinstein, 2005). Vedel (2016)'s literature review replicated this finding, in addition to few medium effect sizes showing that Law, Business, and Economics scored lower in Agreeableness compared to with Medicine, Psychology, Sciences, Arts, and Humanities. Regarding Neuroticism, students in Arts, Humanities, Psychology, Economics, and Business score higher than those in in Engineering, Law, and Sciences (Vedel, 2016). Evidence suggests engineers score higher in Conscientiousness (Clariana, 2017; De Fruyt & Mervielde, 1996; Kline & Lapham, 1992). Vedel (2016)'s also found medium effect sizes with Arts and Humanities scoring lower in Conscientiousness than Sciences, Law, Economics, Engineering, Medicine, and Psychology. Contrary to expectations, not all studies reported arts as the most Open to experience (De Fruyt & Mervielde, 1996; Rubinstein, 2005). Vedel (2016) found medium to large effect

sizes with Humanities, Arts, Psychology, and Political Sciences scoring higher than Economics, Engineering, Law, and Sciences.

In accordance with these results, studies comparing people across occupations have also shown that different jobs attract specific personality profiles. Oh, Han, Holtz, Kim, and Kim (2018), for instance, compared the personality profiles of recently hired members at a pharmaceutical and a banking company and found that they were especially different in Neuroticism ($d=.34$), Openness ($d=.14$), and Conscientiousness ($d=.10$), but less so in Extraversion ($d=.05$) and Agreeableness ($d=-.01$). Lippa (2010), found that at an individual level and controlling for sex, male-preferred occupations attracted individuals with lower levels of Extraversion, Neuroticism, and Agreeableness. Both pieces of research show that different occupational fields attract people with specific personality profiles. Additionally, King et al. (2017) found that employees working within the same occupational field tend to have more similar personality traits compared to other occupational fields.

Summary and hypotheses

Personality differences across occupations have been thoroughly studied. However, most studies have re-categorized occupations into Holland's RIASEC categories rather than using actual occupational titles. Actual occupations could be operationalized in terms of occupational field (e.g.: STEM vs. Non-STEM) or orientation (i.e. Prediger's people-things dimension). These categorization systems are often considered interchangeable (e.g.: Lippa, Preston, & Penner, 2014; Stewart-Williams & Halsey, 2021) but, to our knowledge, no attempts have been made to understand the relation between the two. Moreover, all previous research has focused on personality differences at domain level which might obscure personality differences at lower levels of aggregation (Booth & Irwing, 2011; Del Giudice, Booth, & Irwing, 2012; Kaiser, 2019; Mac Giolla & Kajonius, 2019). Hence, using nuances and facets might provide a more detailed account of the

personality differences between occupations.

In this study we aim to test personality differences at facet and nuance level, using actual occupations categorized according to their field and their orientation. According to previous research, we hypothesize that:

- *Hypothesis 1 (H1)*: If the uneven sex representation in certain occupational fields was influenced by some stable characteristics like personality, the personality traits differentiating men and women should also show prominent differences between these occupational fields. In other words, personality differences across occupations should mirror sex differences in personality.
- *Hypothesis 2 (H2)*: Given that the occupational orientation dimension (Prediger's people-things) could be nested within the occupational field (i.e. STEM vs. Non-STEM) divide, differences in personality traits across occupational orientations will be greater than trait differences between STEM vs Non-STEM.

These questions will be investigated across two studies using independent samples from Estonia (Study 1); as well as China and the UK (Study 2).

Study 1

Methods

Sample

Data were retrieved from the Estonian Genome Centre (EGC) of the University of Tartu including over 51 000 participants representative of the Estonian population (for details see www.biobank.ee). Most participants were randomly recruited by their physicians, although volunteers were also included. Participants signed a consent form (available at www.biobank.ee) and completed a computer-assisted personal interview. A subset of over 3 200 randomly selected participants were asked to additionally fill in a

self-report personality questionnaire.

Materials

Personality. Participants completed the Estonian version of the NEO-PI-3 (De Fruyt et al., 2009; Robert R. McCrae, Costa, & Martin, 2005) which is a slightly modified and more readable version of the Revised NEO Personality Inventory (NEO-PI-R, Paul T. Costa & McCrae, 1992). The NEO-PI-3 has 240 items on a 5-point Likert scale ranging from “completely disagree” to “completely agree.” Items can be grouped into 30 personality facets which can also be summarized into the Big Five domains, such that each domain score is a composite of six facet scores. In addition, informants close to the participants (e.g.: parents, partners, etc.) were asked to complete the Estonian version of the NEO-PI-3 as if they were the participant. Allik et al. (2010) found large convergence between self and informant personality scores across cultures. Moreover, Robert R. McCrae (1994) advised the combination of self and informant-reported personality scores to enhance measurement reliability. Therefore we used both self and informant-reported personality scores in our analyses.

Occupational field. Participants’ self-reported job titles we re-coded to match the 2008 version of the International Standard Classification of Occupations (ISCO-08). ISCO-08 groups jobs into ten broad categories according to occupational level which is generally determined by the education qualification needed. There were two requisites to select the professional and technical occupations that were used required formal education (i.e. university studies or vocational education) as long as they were easily identifiable as pertaining to either STEM or Non-STEM. leaving aside ambiguous groups like “university teachers,” “sports science” (see the supplementary materials). Additionally, occupations in which sex-representation was related to confounding variables like physical strength were also excluded (e.g.: mining).

Analysis

We used R (Version 4.0.2; R Core Team, 2020) and the R-packages *careless* (Version 1.2.1; Richard D. Yentes & Wilhelm, 2021), *corrplot2017* (Wei & Simko, 2017), *dplyr* (Version 1.0.7; Wickham, François, Henry, & Müller, 2021), *e1071* (Version 1.7.6; Meyer, Dimitriadou, Hornik, Weingessel, & Leisch, 2021), *formr* (Version 0.8.5; R. Arslan, 2014), *ggplot2* (Version 3.3.5; Wickham, 2016), *gmodels* (Version 2.18.1; Warnes et al., 2018), *gridExtra* (Version 2.3; Auguie, 2017), *kableExtra* (Version 1.3.4; Zhu, 2021), *knitr* (Version 1.33; Xie, 2015), *lme4* (Version 1.1.26; Bates, Mächler, Bolker, & Walker, 2015), *Matrix* (Version 1.2.18; Bates & Maechler, 2019), *papaja* (Version 0.1.0.9997; Aust & Barth, 2020), *patchwork* (Version 1.1.1; Pedersen, 2020), *psych* (Version 2.0.12; Revelle, 2020), *rcompanion* (Version 2.4.1; Mangiafico, 2021), *readxl* (Version 1.3.1; Wickham & Bryan, 2019), *tidyr* (Version 1.1.3; Wickham, 2021), *tinylabels* (Version 0.2.0; Barth, 2021), and *writexl* (Version 1.3.1; Ooms, 2020) for all our analyses.

Study 1 used a correlated beta approach to measure the degree to which personality differences across fields mirrored personality sex-differences. Specifically, personality scores were first regressed to occupation, sex, and age. This regression model was run separately for personalty scores at the facet and nuance level (i.e. individual items). Occupation and sex were dummy coded so that 1 represented STEM and men, respectively. Therefore, the regression estimate for occupation would reflect the difference in personality scores between STEM and non-STEM, controlling for age and sex. Equivalently, the regression estimate for sex would represent the difference in personality scores between males and females, controlling for occupation and age. Including covariates was crucial for two reasons: (1) to compensate for the potential implications of the uneven sex-distribution in the STEM/non-STEM divide, and (2) to control for potential personality changes associated with the time an individual has been involved in the same field or position (e.g.: Oh, Han, Holtz, Kim, & Kim, 2018). Finally, the sex and occupation beta coefficients were extracted

for each personality measure and correlated. This correlation would reflect the degree to which personality differences across fields mirror the personality differences between men and women.

These analyses were run at nuance and facet level for both self-reported and informant-reported personality scores. Lastly, these results were compared to those using the average between self and informant-reported personality scores at nuance and facet level. Aggregating both sources of information will reduce the measurement error, providing more reliable results.

Results and discussion

Table 1 shows the number of observations per sex according to the occupational field and occupational status (i.e. professional or technical occupations). The sample size difference between non-STEM and STEM was noticeable, although this should be expected given the limited number of positions included in STEM.

First, we correlated self and informant-reported personality items at both, nuance ($M=.29$, $SD=.09$) and facet level ($M=.46$, $SD=0.08$). Correlations at the facet level tended to be higher than at nuance level, possibly because of higher reliability of facet-level data which results when aggregating nuances' common variance at the expense of their specific variance.

Table 2 shows the Spearman's correlation (ρ) between sex and occupational field regression estimates when predicting self- or informant-reported personality scores at nuance level. As Table 2 shows, there was a small and non-significant correlation between the sex and occupation regression estimates ($\rho = .02$, $CI = [-.15, .19]$ for self-reported and $\rho = .12$, $CI = [-.05, .28]$, for informant-reported). Similar results were found when using personality scores at the facet level as the outcome variable: $\rho = .09$, $CI = [-.39, .53]$ for self-reported and $\rho = .19$, $CI = [-.30, .60]$ for informant-reported personality scores.

Interestingly, there was a high - and significant - correlation between the self and informant-reported regression estimates for occupation ($\rho = .50$ at nuance and $\rho = .75$ at facet level) and sex ($\rho = .69$ at nuances and $\rho = .75$ at facet level), showing that personality differences between sexes and STEM/Non-STEM replicated across both sources of information. This justified averaging the personality scores from both sources of information: self-reported and informant-reported personality scores. Using this average of personality scores as the outcome variable replicated previous results. The Spearman's correlation between the occupation and sex regression estimates was $.13$, $p = .04$ at the nuance level and $.21$, $p = .26$ at facet level.

Overall and contrary to Hypothesis 1, the correlation between the occupation and sex regression estimates was not strong enough to claim that personality differences between fields mirror personality sex-differences, regardless of who reported the personality scores (i.e. self- or informant- reported) and of their aggregation level (i.e. nuance or facet level).

Study 2

Methods

Sample

This study uses a subset of a larger sample collected in the UK, Russia, and China. A survey containing questions on various life outcomes together with a personality questionnaire was uploaded to Formr (R. C. Arslan, Walther, & Tata, 2020) and was distributed through social media (e.g.: Twitter, Facebook, Instagram, etc.) as well as in Prolific. A total of 1607 UK participants and 2495 Chinese participants started the survey. Out of those, only 1221 UK and 1405 Chinese participants reached the personality items and provided an occupational title that could be codified.

All participants under 18 years-old ($N = 64$ UK and $N = 78$ Chinese participants) were eliminated. After examining data quality with R's *careless* package (R. D. Yentes &

Wilhelm, 2018), another 14 UK participants and 48 Chinese participants were eliminated for giving the same answer 10 or more consecutive times in the personality questionnaire. This left a total of 1143 UK participants (58% Women) and 1279 Chinese participants (73% Women). Table 3 shows the samples' demographics.

Materials

Personality. A total of 90 items were selected from the pool of items created by Henry, Möttus, & Vainik (in preparation). Items were mainly retrieved from the International Personality Item Pool (IPIP, Goldberg, 1999) and the Synthetic Aperture Personality Assessment (SAPA, Condon, 2018). Some items were written by the authors. Items were selected to maximize their re-test reliability ($M=.71$, $SD=.09$, Values range=.60-.85), their clarity, readability, as well as to minimize their redundancy. Following Condon et al. (2021) advice, items were selected and categorized into facets according to: (1) their re-test reliability, (2) feedback from Dr McCrae, and (3) fit within the IPIP's facet definitions. Domain scores were computed as the average across six facet scores, each computed as the sum scores of three items (see the full list of items at <https://osf.io/xeqch/>).

Note that only self-reported personality scores were available for Study 2. Although Study 1 and Study 2 used different personality measures, both included nuances and facets of the Big Five.

Occupational Field. Study 2 classified occupations using the same procedure and category system (i.e. ISCO-08) used in Study 1. Hence, Study 2 used the same occupations that were included in Study 1. Self-reported occupations were re-coded by two independent researchers per sample (cross-rater agreement was .50 for the UK sample and .55 for the Chinese sample), disagreements were discussed until consensus was reached. In the UK there were 130 participants working in STEM and 285 working in Non-STEM occupations.

In the Chinese sample there were 74 participants working in STEM and 404 working in Non-STEM occupations (Table 4). Not all participants in this study

Occupational Orientation. Occupational orientation was measured by asking participants how much time they spend working with people/animals compared to the time they invest working with things (e.g.: computers, machines, etc.). The actual item label was:

“Thinking about your job, how much time do you spend working with people/animals and things? You can use the slider to mark the percentage of time you devote working with people or animals. The remaining percentage will be the time you use to work with things. For example, if you move the slider to 40, it would mean that you expend 40% of the time working with people and 60% working with things.”

The answer options showed some examples of “working with people/animals” and “working with things.” To facilitate the comparison of occupational field and orientation – and given that STEM occupations have often been considered things-oriented – this item was reversed so it reflected the percentage of time invested working with things.

Analysis

Study 2 had two aims: replicating Study 1 and expanding it by operationalizing occupation as occupational orientation (i.e. Prediger’s people-things dimension). To replicate Study 1, each personality score (either at nuance or facet level) was regressed to occupation (1=STEM, 0= Non-STEM), sex (1= men, 0= female), and age. The sex and occupation regression estimates were extracted for each personality measure and correlated. Analyses were run separately for the UK and the Chinese samples. Afterwards, to expand this replication, occupation was operationalized as occupational orientation (i.e. high values corresponding to things-orientated occupations). Additionally, the correlation between occupational field and orientation was also computed (polyserial

correlation) to empirically test whether occupational field and orientation were equivalent categories.

Results and discussion

Table 5 shows the Spearman's correlation (ρ) between the occupation and sex regression estimates when predicting personality nuances or facets for both the UK and the Chinese samples. These results largely replicated Study 1. On the one hand, correlations at the facet level ($\rho_{UK} = -.17$, $CI = [-.59, .31]$ and $\rho_{China} = .22$, $CI = [-.27, .62]$) were stronger than at the nuance level ($\rho_{UK} = -.12$, $CI = [-.38, .15]$ and $\rho_{China} = .15$, $CI = [-.13, .40]$). On the other hand, these correlations were small. Surprisingly, the direction of the regression estimates correlations was not consistent across samples (i.e. correlations were negative in the UK sample but not in the Chinese sample). These small correlations could be due to random variation but it could also reflect a consistent cultural difference. This will be further explored in the General Discussion. Overall, all correlations in Study 2 were slightly larger than in Study 1, but would still be classified as small effects.

Study 1 and 2 results showed a non-meaningful fluctuation around zero. In this sense, results of Study 2 replicate Study 1: the correlation between the occupation and sex regression estimates was not strong enough to claim that personality differences between fields mirror personality sex-differences at nuance or facet level.

Regarding the relationship between occupational field and orientation, the polyserial correlation in both samples was small ($r = -.01$ in the UK sample and $r = 0.16$ in the Chinese sample), meaning that occupational field and orientation are not interchangeable. In other words, many people in STEM occupations spend more time working with people than with things and, conversely, many people in Non-STEM occupations spend more time working with things than with people.

The results from the regression estimates correlations between sex and occupational

orientation are presented in Table 6 for both the UK and the Chinese samples. The strength of the correlation was notably higher for the UK sample (at nuance level $r=.27$, $CI=[.00,.51]$ and facet level $r=.33$, $CI=[-.17, .69]$) compared to the Chinese sample (at nuance level $r=.03$, $CI=[-.24,.30]$ and facet level $r=.08$, $CI=[-.39, .52]$).

General Discussion

Holland's (1959) theory of personality-environment typology, as well as Gottfredson's (1981) theory of Circumscription and Compromise, suggest that people partly shape their occupational aspirations to match their interests and personality traits. Recently, Stewart-Williams and Halsey (2021) reviewed the evidence on sex-segregation in the labor market and concluded that the psychological make up differentiating each sex could be contributing to this divide.

This study address this idea by studying the degree to which personality differences across occupations mirrored personality sex differences. Previous research testing this relationship has not used actual occupational titles but Holland's RIASEC categories. Additionally, personality differences have only been considered at domain level. To tackle these limitations, occupation was operationalized as field (STEM vs. Non-STEM) and as orientation (i.e. Prediger's people-things dimension). Additionally, personality scores at nuance and facet level were used. The analyses consisted in, first, regressing the personality scores to sex, age, and occupation; and then, extracting and correlating the sex and occupation regression estimates for each personality measure. These analyses were replicated in three samples.

Study 1 used an Estonian sample and, contrary to Hypothesis 1, found no evidence that personality differences across occupational fields mirrored personality sex differences either when using self-reported or informant-reported personality scores at nuance or at facet level. This result was replicated in Study 2, using a UK and Chinese sample of

self-reported personality scores at nuance and facet level. This evidences that the way in which occupation had previously been operationalized – especially when using RIASEC categories (e.g.: Hoff, Song, Einarsdóttir, Briley, & Rounds, 2020; Hunalp, 2020; Larson, Rottinghaus, & Borgen, 2002; Mount, Barrick, Scullen, & Rounds, 2005) – was likely inflating the correlation between occupations and personality traits.

Study 2 expanded this replication by (1) testing the correlation between occupational field and orientation; and (2) substituting occupational field by occupational orientation. Occupational field and orientation were not correlated implying that, contrary to popular belief, STEM occupations do not necessary involve working exclusively with computers, materials, data, etc. Conversely, Non-STEM occupations do not require constant interaction with other people. Hence, these results corroborated what some previous research had roughly suggested (Hustad, Bandholtz, Herlitz, & Dekhtyar, 2020; Lippa, Preston, & Penner, 2014).

Moreover, results from Study 2 indicate that personality sex differences do mirror personality differences across occupational orientations, at least, in the UK sample. Thus, these results partially supported Hypothesis 2. Given that there seemed to be no relationship between occupational field and occupational orientation, it could be that other psychological variables (e.g.: intelligence, spatial ability, etc.) drive people into different field but it is personality what pushes individuals toward more people- or things-oriented jobs. As previous research shows less sex differences in collectivists countries (Paul T. Costa, Terracciano, & McCrae, 2001; Kaiser, 2019; Schmitt, Realo, Voracek, & Allik, 2008), it could be that this trend was not as evident in the Chinese sample due to a range restriction in the personality sex differences. On the other hand, the results from Study 2 might be reflecting consistent cultural differences between the UK and China labor markets. For example, in China, personality may be more relevant for choosing the occupational field than occupational orientation.

Overall, our results highlight the need to contemplate how variables are operationalized, especially as it regards to occupations. For instance, using broader fields, rather than STEM vs. Non-STEM might reflect more nuanced personality differences across occupations. Furthermore, certain operationalizations might not be as relevant across contexts to study their relationship to the human psyche - e.g.: occupational orientation might provide more information than occupational field. Lastly, albeit further replications are needed, Study 2 results seem to echo Holland and Gottfredson theories on occupational choice, and how they could be shaped by the interplay between intelligence, personality, and the surrounding context.

Strengths and limitations

The Chinese and UK samples were small, so further replications are needed. In fact, the contradicting results on personality differences across sex and occupational orientation might be due to the small sample sizes. Future studies would be necessary to confirm whether these results on occupational orientation reflected an actual cultural difference. Another limitation of this study is the recategorization of self-reported occupational titles into ISCO-08 categories. Although ISCO-08 is a comprehensive categorization system, it still involves a substantial amount of subjectivity. Following studies might obtain more accurate codes by allowing participants to select the codes that best represented their position.

Nonetheless, this study counts with numerous strengths. The most noticeable strength is the replication of results across three samples, across self and informant-reported personality scores at nuance and facet level. Hence, the evidence regarding personality differences across sex and occupational field seems robust. Additionally, this study also tackled numerous limitations of previous research such as using actual occupations and exploring personality differences at nuance and facet level. Moreover, this line of research has enormous potential to explain uneven sex-representation

476 across fields (Ceci, Ginther, Kahn, & Williams, 2014), and even to improve vocational
477 counseling and job stability (Lubinski, 2000; Wilk, Desmarais, & Sackett, 1995).

References

- Allik, J., Realo, A., Mõttus, R., Borkenau, P., Kuppens, P., & Hřebíčková, M. (2010). How people see others is different from how people see themselves: A replicable pattern across cultures. *Journal of Personality and Social Psychology*, 99(5), 870–882. <https://doi.org/10.1037/a0020963>
- Arslan, R. (2014). *Formr: Formr survey framework*.
- Arslan, R. C., Walther, M. P., & Tata, C. S. (2020). Formr: A study framework allowing for automated feedback generation and complex longitudinal experience-sampling studies using R. *Behavior Research Methods*, 52(1), 376–387. <https://doi.org/10.3758/s13428-019-01236-y>
- Auguie, B. (2017). *gridExtra: Miscellaneous functions for "grid" graphics*. Retrieved from <https://CRAN.R-project.org/package=gridExtra>
- Aust, F., & Barth, M. (2020). *papaja: Prepare reproducible APA journal articles with R Markdown*. Retrieved from <https://github.com/crsh/papaja>
- Barth, M. (2021). *tinylabels: Lightweight variable labels*. Retrieved from <https://github.com/mariusbarth/tinylabels>
- Bates, D., & Maechler, M. (2019). *Matrix: Sparse and dense matrix classes and methods*. Retrieved from <https://CRAN.R-project.org/package=Matrix>
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48. <https://doi.org/10.18637/jss.v067.i01>
- Benbow, C. P., Lubinski, D., Shea, D. L., & Eftekhari-Sanjani, H. (2000). Sex Differences in Mathematical Reasoning Ability at Age 13: Their Status 20 Years

Later. *Psychological Science*, 11(6), 474–480.

<https://doi.org/10.1111/1467-9280.00291>

Booth, T., & Irwing, P. (2011). Sex differences in the 16PF5, test of measurement invariance and mean differences in the US standardisation sample. *Personality and Individual Differences*, 50(5), 553–558.

<https://doi.org/10.1016/j.paid.2010.11.026>

Bordin, E. S. (1943). A Theory of Vocational Interests as Dynamic Phenomena'. *Educational and Psychological Measurement*, 3(1), 46–62.

<https://doi.org/10.1177/001316444300300105>

Ceci, S. J., Ginther, D. K., Kahn, S., & Williams, W. M. (2014). Women in Academic Science: A Changing Landscape. *Psychological Science in the Public Interest*, 15(3), 75–141. <https://doi.org/10.1177/1529100614541236>

Clariana, M. (2017). Personalidad, Procrastinación y Conducta Deshonesta en Alumnado de distintos Grados Universitarios. *Electronic Journal of Research in Education Psychology*, 11(30). <https://doi.org/10.14204/ejrep.30.13030>

Condon, D. M. (2018). *The SAPA Personality Inventory: An empirically-derived, hierarchically-organized self-report personality assessment model*.

<https://doi.org/10.31234/osf.io/sc4p9>

Condon, D. M., Wood, D., Möttus, R., Booth, T., Costantini, G., Greiff, S., ...

Zimmermann, J. (2021). Bottom Up Construction of a Personality Taxonomy. *European Journal of Psychological Assessment*, 36(6), 923–934.

<https://doi.org/10.1027/1015-5759/a000626>

Costa, Paul T., & McCrae, R. R. (1992). Professional manual: Revised NEO personality inventory (NEO-PI-R) and NEO five-factor inventory (NEO-FFI).

Odessa, FL: *Psychological Assessment Resources*, 61.

Costa, Paul T., Terracciano, A., & McCrae, R. R. (2001). Gender differences in personality traits across cultures: Robust and surprising findings. *American Psychological Association*, 81(2), 322–331.
<https://doi.org/10.1037/0022-3514.81.2.322>

Croll, P. (2008). Occupational choice, socio-economic status and educational attainment: A study of the occupational choices and destinations of young people in the British Household Panel Survey. *Research Papers in Education*, 23(3), 243–268. <https://doi.org/10.1080/02671520701755424>

De Fruyt, F., De Bolle, M., McCrae, R. R., Terracciano, A., Costa, P. T., & Collaborators of the Adolescent Personality Profiles of Cultures Project. (2009). Assessing the Universal Structure of Personality in Early Adolescence: The NEO-PI-R and NEO-PI-3 in 24 Cultures. *Assessment*, 16(3), 301–311.
<https://doi.org/10.1177/1073191109333760>

De Fruyt, F., & Mervielde, I. (1996). Personality and interests as predictors of educational streaming and achievement. *Wiley Online Library*, 10(5), 405–425.
[https://doi.org/10.1002/\(sici\)1099-0984\(199612\)10:5%3C405::aid-per255%3E3.0.co;2-m](https://doi.org/10.1002/(sici)1099-0984(199612)10:5%3C405::aid-per255%3E3.0.co;2-m)

Dekhtyar, S., Weber, D., Helgertz, J., & Herlitz, A. (2018). Sex differences in academic strengths contribute to gender segregation in education and occupation: A longitudinal examination of 167,776 individuals. *Intelligence*, 67, 84–92. <https://doi.org/10.1016/j.intell.2017.11.007>

Del Giudice, M., Booth, T., & Irwing, P. (2012). The Distance Between Mars and Venus: Measuring Global Sex Differences in Personality. *PLoS ONE*, 7(1),

e29265. <https://doi.org/10.1371/journal.pone.0029265>

Ellis, L., Ratnasingam, M., & Wheeler, M. (2012). Gender, sexual orientation, and occupational interests: Evidence of their interrelatedness. *Personality and Individual Differences*, 53(1), 64–69. <https://doi.org/10.1016/j.paid.2012.02.008>

Feingold, A. (1994). Gender Differences in Personality: A Meta-Analysis. *American Psychological Association*, 116(3), 429–456. <https://doi.org/10.1016/j.paid.2007.05.004>

Goldberg, L. R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. *Personality Psychology in Europe*, 7(1), 7–28.

Gore, J., Holmes, K., Smith, M., Fray, L., McElduff, P., Weaver, N., & Wallington, C. (2017). Unpacking the career aspirations of Australian school students: Towards an evidence base for university equity initiatives in schools. *Higher Education Research & Development*, 36(7), 1383–1400. <https://doi.org/10.1080/07294360.2017.1325847>

Gore, J., Holmes, K., Smith, M., Southgate, E., & Albright, J. (2015). Socioeconomic status and the career aspirations of Australian school students: Testing enduring assumptions. *The Australian Educational Researcher*, 42(2), 155–177. <https://doi.org/10.1007/s13384-015-0172-5>

Gottfredson, L. S. (1981). Circumscription and Compromise: A Developmental Theory of Occupational Aspirations. *Journal of Counseling Psychology*, 28(6), 545–579. <https://doi.org/10.1037/0022-0167.28.6.545>

Heineck, G. (2011). Does it pay to be nice? Personality and earnings in the united kingdom. *ILR Review*, 64(5), 1020–1038.

<https://doi.org/10.1177/001979391106400509>

Hoff, K. A., Briley, D. A., Wee, C. J. M., & Rounds, J. (2018). Normative changes in interests from adolescence to adulthood: A meta-analysis of longitudinal studies. *Psychological Bulletin*, 144(4), 426–451. <https://doi.org/10.1037/bul0000140>

Hoff, K. A., Song, Q. C., Einarsdóttir, S., Briley, D. A., & Rounds, J. (2020). Developmental structure of personality and interests: A four-wave, 8-year longitudinal study. *Journal of Personality and Social Psychology*, 118(5), 1044–1064. <https://doi.org/10.1037/pspp0000228>

Holland, J. L. (1959). A theory of vocational choice. *Journal of Counseling Psychology*, 6(1), 35–45. <https://doi.org/10.1037/h0040767>

Holmes, K., Gore, J., Smith, M., & Lloyd, A. (2018). An Integrated Analysis of School Students' Aspirations for STEM Careers: Which Student and School Factors Are Most Predictive? *International Journal of Science and Mathematics Education*, 16(4), 655–675. <https://doi.org/10.1007/s10763-016-9793-z>

Howard, K. A. S., Carlstrom, A. H., Katz, A. D., Chew, A. Y., Ray, G. C., Laine, L., & Caulum, D. (2011). Career aspirations of youth: Untangling race/ethnicity, SES, and gender. *Journal of Vocational Behavior*, 79(1), 98–109. <https://doi.org/10.1016/j.jvb.2010.12.002>

Hunalp, B. I. (2020). *What happens in rich and gender egalitarian countries: A systematic review of gender differences across 6 features in order to explain STEM gender disparity*. <https://doi.org/10.13140/RG.2.2.31970.35521>

Hustad, I. B., Bandholtz, J., Herlitz, A., & Dekhtyar, S. (2020). Occupational Attributes and Occupational Gender Segregation in Sweden: Does It Change Over Time? *Frontiers in Psychology*, 11.

<https://doi.org/10.3389/fpsyg.2020.00554>

Kaiser, D. T. (2019). Nature and evoked culture: Sex differences in personality are uniquely correlated with ecological stress. *Personality and Individual Differences*, 148, 67–72. <https://doi.org/10.31234/osf.io/u73gh>

Kajonius, P., & Mac Giolla, E. (2017). Personality traits across countries: Support for similarities rather than differences. *PLOS ONE*, 12(6), e0179646. <https://doi.org/10.1371/journal.pone.0179646>

Kaufman, J. C., Pumacahua, T. T., & Holt, R. E. (2013). Personality and creativity in realistic, investigative, artistic, social, and enterprising college majors. *Personality and Individual Differences*, 54(8), 913–917. <https://doi.org/10.1016/j.paid.2013.01.013>

King, D. D., Ott-Holland, C. J., Ryan, A. M., Huang, J. L., Wadlington, P. L., & Elizondo, F. (2017). Personality Homogeneity in Organizations and Occupations: Considering Similarity Sources. *Journal of Business and Psychology*, 32(6), 641–653. <https://doi.org/10.1007/s10869-016-9459-4>

Kline, P., & Lapham, S. L. (1992). Personality and faculty in British universities. *Personality and Individual Differences*, 13(7), 855–857. [https://doi.org/10.1016/0191-8869\(92\)90061-S](https://doi.org/10.1016/0191-8869(92)90061-S)

Larson, L. M., Rottinghaus, P. J., & Borgen, F. H. (2002). Meta-analyses of Big Six Interests and Big Five Personality Factors. *Journal of Vocational Behavior*, 61(2), 217–239. <https://doi.org/10.1006/jvbe.2001.1854>

Lippa, R. A. (1998). Gender-Related Individual Differences and the Structure of Vocational Interests: The Importance of the People-Things Dimension. *Journal of Personality and Social Psychology*, 74(4), 996–1009.

<https://doi.org/10.1037/0022-3514.74.4.996>

Lippa, R. A. (2005). Sexual orientation and personality. *Annual Review of Sex Research*, 16(1), 119–153. <https://doi.org/10.1080/10532528.2005.10559831>

Lippa, R. A. (2008). Sex Differences and Sexual Orientation Differences in Personality: Findings from the BBC Internet Survey. *Archives of Sexual Behavior*, 37(1), 173–187. <https://doi.org/10.1007/s10508-007-9267-z>

Lippa, R. A. (2010). Sex Differences in Personality Traits and Gender-Related Occupational Preferences across 53 Nations: Testing Evolutionary and Social-Environmental Theories. *Archives of Sexual Behavior*, 39(3), 619–636. <https://doi.org/10.1007/s10508-008-9380-7>

Lippa, R. A. (2020). Interest, Personality, and Sexual Traits That Distinguish Heterosexual, Bisexual, and Homosexual Individuals: Are There Two Dimensions That Underlie Variations in Sexual Orientation? *Archives of Sexual Behavior*, 49(2), 607–622. <https://doi.org/10.1007/s10508-020-01643-9>

Lippa, R. A., Preston, K., & Penner, J. (2014). Women’s Representation in 60 Occupations from 1972 to 2010: More Women in High-Status Jobs, Few Women in Things-Oriented Jobs. *PLoS ONE*, 9(5), e95960. <https://doi.org/10.1371/journal.pone.0095960>

Low, K. S. D., Yoon, M., Roberts, B. W., & Rounds, J. (2005). The Stability of Vocational Interests From Early Adolescence to Middle Adulthood: A Quantitative Review of Longitudinal Studies. *Psychological Bulletin*, 131(5), 713–737. <https://doi.org/10.1037/0033-2909.131.5.713>

Lubinski, D. (2000). Scientific and Social Significance of Assessing Individual Differences: “Sinking Shafts at a Few Critical Points.” *Annual Review of*

645 *Psychology*, 51(1), 405–444. <https://doi.org/10.1146/annurev.psych.51.1.405>

646 Lubinski, D., & Benbow, C. P. (1992). Gender Differences in Abilities and
647 Preferences Among the Gifted: Implications for the Math-Science Pipeline.
648 *Current Directions in Psychological Science*, 1(2), 61–66.
649 <https://doi.org/10.1111/1467-8721.ep11509746>

650 Luoto, S. (2020). Sex differences in people and things orientation are reflected in sex
651 differences in academic publishing. *Journal of Informetrics*, 14(2), 101021.
652 <https://doi.org/10.1016/j.joi.2020.101021>

653 Mac Giolla, E., & Kajonius, P. J. (2019). Sex differences in personality are larger in
654 gender equal countries: Replicating and extending a surprising finding.
655 *International Journal of Psychology*, 54(6), 705–711.
656 <https://doi.org/10.1002/ijop.12529>

657 Mangiafico, S. (2021). *Rcompanion: Functions to support extension education*
658 *program evaluation*. Retrieved from
659 <https://CRAN.R-project.org/package=rcompanion>

660 McCrae, Robert R. (1994). The Counterpoint of Personality Assessment: Self
661 Reports and Observer Ratings. *Assessment*, 1(2), 159–172.
662 <https://doi.org/10.1177/1073191194001002006>

663 McCrae, Robert R. (2015). A More Nuanced View of Reliability: Specificity in the
664 Trait Hierarchy. *Personality and Social Psychology Review*, 19, 97–112.
665 <https://doi.org/10.1177/1088868314541857>

666 McCrae, Robert R., Costa, P. T., Jr., & Martin, T. A. (2005). The NEOPI: A More
667 Readable Revised NEO Personality Inventory. *Journal of Personality*
668 *Assessment*, 84(3), 261–270. https://doi.org/10.1207/s15327752jpa8403_05

Meyer, D., Dimitriadou, E., Hornik, K., Weingessel, A., & Leisch, F. (2021). *e1071: Misc functions of the department of statistics, probability theory group (formerly: E1071), TU wien*. Retrieved from <https://CRAN.R-project.org/package=e1071>

Mount, M. K., Barrick, M. R., Scullen, S. M., & Rounds, J. (2005). Higher-order dimensions of the Big Five personality traits and the Big Six vocational interest types. *Personnel Psychology*, 58(2), 447–478.
<https://doi.org/10.1111/j.1744-6570.2005.00468.x>

Murphy, S. A., Fisher, P. A., & Robie, C. (2020). International Comparison of Gender Differences in the Five Factor Model of Personality: An Investigation Across 105 Countries. *Journal of Research in Personality*, 104047.
<https://doi.org/10.1016/j.jrp.2020.104047>

Oh, I.-S., Han, J. H., Holtz, B., Kim, Y. J., & Kim, S. (2018). Do birds of a feather flock, fly, and continue to fly together? The differential and cumulative effects of attraction, selection, and attrition on personality-based within-organization homogeneity and between-organization heterogeneity progression over time. *Journal of Organizational Behavior*, 39(10), 1347–1366.
<https://doi.org/10.1002/job.2304>

Ooms, J. (2020). *Writexl: Export data frames to excel 'xlsx' format*. Retrieved from <https://CRAN.R-project.org/package=writexl>

Pedersen, T. L. (2020). *Patchwork: The composer of plots*. Retrieved from <https://CRAN.R-project.org/package=patchwork>

Prediger, D. J. (1982). Dimensions underlying Holland's hexagon: Missing link between interests and occupations? *Journal of Vocational Behavior*, 21(3), 259–287. [https://doi.org/10.1016/0001-8791\(82\)90036-7](https://doi.org/10.1016/0001-8791(82)90036-7)

- R Core Team. (2020). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from <https://www.R-project.org/>
- Revelle, W. (2020). *Psych: Procedures for psychological, psychometric, and personality research*. Evanston, Illinois: Northwestern University. Retrieved from <https://CRAN.R-project.org/package=psych>
- Rubinstein, G. (2005). The big five among male and female students of different faculties. *Personality and Individual Differences*, 38(7), 1495–1503. <https://doi.org/10.1016/j.paid.2004.09.012>
- Schmitt, D. P., Realo, A., Voracek, M., & Allik, J. (2008). Why can't a man be more like a woman? Sex differences in Big Five personality traits across 55 cultures. *Journal of Personality and Social Psychology*, 94(1), 168–182. <https://doi.org/10.1037/0022-3514.94.1.168>
- Stewart-Williams, S., & Halsey, L. G. (2021). Men, women and STEM: Why the differences and what should be done? *European Journal of Personality*, 35(1), 3–39. <https://doi.org/10.1177/0890207020962326>
- Stoet, G., & Geary, D. C. (2013). Sex Differences in Mathematics and Reading Achievement Are Inversely Related: Within- and Across-Nation Assessment of 10 Years of PISA Data. *PLoS ONE*, 8(3), e57988. <https://doi.org/10.1371/journal.pone.0057988>
- Stoet, G., & Geary, D. C. (2018). The Gender-Equality Paradox in Science, Technology, Engineering, and Mathematics Education. *Psychological Science*, 29(4), 581–593. <https://doi.org/10.1177/0956797617741719>
- Su, R., Rounds, J., & Armstrong, P. I. (2009). Men and things, women and people:

A meta-analysis of sex differences in interests. *Psychological Bulletin*, 135(6), 859–884. <https://doi.org/10.1037/a0017364>

Vedel, A. (2016). Big Five personality group differences across academic majors: A systematic review. *Personality and Individual Differences*, 92, 1–10. <https://doi.org/10.1016/j.paid.2015.12.011>

Warnes, G. R., Bolker, B., Lumley, T., Randall C. Johnson are Copyright SAIC-Frederick, R. C. Johnson. C. from, Intramural Research Program, Inc. F. by the, NIH, of the, . . . Cancer Research under NCI Contract NO1-CO-12400., C. for. (2018). *Gmodels: Various r programming tools for model fitting*. Retrieved from <https://CRAN.R-project.org/package=gmodels>

Wei, T., & Simko, V. (2017). *R package "corrplot": Visualization of a correlation matrix*. Retrieved from <https://github.com/taiyun/corrplot>

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. Retrieved from <https://ggplot2.tidyverse.org>

Wickham, H. (2021). *Tidyr: Tidy messy data*. Retrieved from <https://CRAN.R-project.org/package=tidyr>

Wickham, H., & Bryan, J. (2019). *Readxl: Read excel files*. Retrieved from <https://CRAN.R-project.org/package=readxl>

Wickham, H., François, R., Henry, L., & Müller, K. (2021). *Dplyr: A grammar of data manipulation*. Retrieved from <https://CRAN.R-project.org/package=dplyr>

Wilk, S. L., Desmarais, L. B., & Sackett, P. R. (1995). Gravitation to Jobs Commensurate With Ability: Longitudinal and Cross-Sectional Tests. *American Psychological Association*, 80(1), 79–85.

740 <https://doi.org/10.1037/0021-9010.80.1.79>

741 Xie, Y. (2015). *Dynamic documents with R and knitr* (2nd ed.). Boca Raton,
742 Florida: Chapman; Hall/CRC. Retrieved from <https://yihui.org/knitr/>

743 Yentes, R. D., & Wilhelm, F. (2018). *Careless: Procedures for computing indices of*
744 *careless responding*.

745 Yentes, Richard D., & Wilhelm, F. (2021). *Careless: Procedures for computing*
746 *indices of careless responding*.

747 Zhu, H. (2021). *kableExtra: Construct complex table with 'kable' and pipe syntax*.
748 Retrieved from <https://CRAN.R-project.org/package=kableExtra>

Table 1

Frequency of Estonian occupations according to sex, occupational status and occupational field.

	STEM		Non-STEM		Total
	Professionals	Technicians	Professionals	Technicians	
Men	123	48	196	59	426
Women	62	17	617	268	964
Total	185	65	813	327	1390

Notes. STEM= Science, Technology, Engineering, and Mathematics.

Table 2

Correlations between the sex and occupational field regression estimates when predicting self- or informant-reported personality scores at nuance level.

		Self-report		Informant-report	
		Occupation R.E.	Sex R.E.	Occupation R.E.	Sex R.E.
Self-report	Occupation R.E.	1			
	Sex R.E.	.02	1		
Informant-report	Occupation R.E.	.50	.08	1	
	Sex R.E.	.22	.69	.12	1

Notes. R.E.= Regression Estimates.

Table 3

Frequencies and descriptive statistics of the UK and Chinese samples.

Variable	N	Percent of the total sample	M	SD
UK Sample				
Sex	1143	100		
Women	659	58.0		
Men	469	42.0		
Age	1143	100	35.64	11.15
Income	1142	99.9	3.58	1.50
No income	128	11.2		
<10 000 pounds	186	16.3		
10 001 -18 000 pounds	199	17.4		
18 001 - 26 000 pounds	250	21.9		
26 001 - 44 000 pounds	278	24.3		
>44 000 pounds	101	8.8		
Education	1143	100	4.65	1.02
No educational qualifications	2	.17		
Primary school	4	.35		
Secondary school	210	18.4		
Vocational Education or Ap- prenticeship	186	16.3		
Undergraduate Education	511	44.7		
Postgraduate Education	230	20.12		

Variable	N	Percent of the total sample	M	SD
Prediger's people-things dimension	1108	96.9	51.16	32.71
Chinese Sample				
Sex	864	100		
Women	931	74.1		
Men	326	25.9		
Age	864	100	28.75	7.34
Income	859	99.4	3.73	2.00
No income	251	19.7		
<10 000 yuan	211	16.6		
10 001 -18 000 yuan	181	14.2		
18 001 - 26 000 yuan	71	5.6		
26 001 - 44 000 yuan	109	8.6		
>44 000 yuan	451	35.4		
Education	861	99.7	5.24	.75
No educational qualifications	1	.01		
Primary school	4	.03		
Secondary school	26	.02		
Vocational Education or Apprenticeship	128	10.0		
Undergraduate Education	610	47.8		
Postgraduate Education	507	39.7		

Variable	N	Percent of the total sample	M	SD
Prediger's people-things dimension	853	71.6	38.23	20.42

Table 4

Frequency of UK and Chinese occupations according to sex, occupational status and occupational field.

			STEM		Non-STEM		Total
			Professionals	Technicians	Professionals	Technicians	
UK	Men	39	25	72	23		159
	Women	45	20	113	74		252
Total		84	45	185	97		411
China	Men	28	7	46	17		98
	Women	23	14	305	32		374
Total		51	21	351	49		472

Notes. STEM= Science, Technology, Engineering, and Mathematics.

Table 5

Correlation between the regression betas of occupation (STEM vs. Non-STEM) and sex when using personality scores at item and facet level

	Item level	Facet level
UK Spearman's rho	-0.13	-0.17
China Spearman's rho	0.15	0.22

Table 6

Correlation between the regression betas of occupation (i.e. Prediger) and sex when using personality scores at item and facet level

	Item level	Facet level
UK Spearman's rho	0.27	0.33
China Spearman's rho	0.03	0.08