AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Applied Psychology

ISSN: 0021-9010

https://doi.org/10.1037/apl0001249

Personality Profiles of 263 Occupations

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While personality trait assessments are widely used in candidate selection, coaching, and occupational counseling, little published research has systematically compared occupations in personality traits. Using a comprehensive personality assessment, we mapped 263 occupations in self-reported Big Five domains and various personality nuances in a sample of 68,540 individuals and cross-validated the findings in informant ratings of 19,989 individuals. Controlling for age and gender, occupations accounted for 2%–7% of Big Five variance in both self-reports and informant reports. Most occupations' average Big Five levels were intuitive, replicated across rating methods, and were consistent with those previously obtained with a brief assessment in a different sociocultural context. Often, they also tracked the Occupational Information Network database's work style ratings and clustered along the International Standard Classification of Occupation's hierarchical framework. Finally, occupations with higher average levels of the personality domains typically linked to better job performance tended to be more homogeneous in these domains, suggesting that jobs with higher performing incumbents are often more selective for personality traits. Several personality nuances had intuitive occupational differences that were larger than those of the Big Five domains (explaining up to 12% variance) and replicated well across rating methods, providing more detailed insights into how job incumbents vary in personality. We provide an interactive application for exploring the results (https://apps.psych.ut.ee/JobProfiles/) and discuss the findings' theoretical and practical implications.

Keywords: personality, occupation, person–job fit, job, Big Five

In many societies, people tend to devote much of their adult life to work, so a systematic understanding of the match between people's traits and their work is both practically and theoretically important (Kristof-Brown et al., 2005). For example, career planning, job applicant selection, and coaching are among the primary applications of personality research, while their success hinges on understanding how people's traits actually vary with occupations. Likewise, the importance of personality traits is often illustrated by their ability to predict key life outcomes (Roberts et al., 2007), among which occupational choice ranks particularly high. However, while psychologists have already carefully mapped mean personality differences across many human categories, including gender (e.g., Schmitt et al., 2008) and age groups (e.g., Bleidorn et al., 2022), cohorts (e.g., Brandt et al., 2022; Smits et al., 2011), or geographical regions (e.g., Allik et al., 2017; Rentfrow & Jokela, 2019), surprisingly little systematic research has been dedicated to personality differences across occupations.

Several studies have described incumbents' typical personality traits in one or a few occupations (Booth et al., 2016; Cerasa et al., 2016; Furnham, 2017; R. King et al., 2011; Lan et al., 2021; Lounsbury et al., 2012, 2016; Oh et al., 2018; Slišković et al., 2022), often with relatively small samples. While organizations that offer assessment services likely hold comprehensive databases about occupational variations in personality traits, they monetize this information and are therefore unlikely to publish it. We know of only two published, larger scale studies systematically mapping traits across a broader range of occupations. One reported mean differences in the Big Five personality domains across

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This article has been presented at the European Conference of Personality, held in Berlin from August 6 to 9, 2024. The article was previously posted as a preprint on PsyArXiv at https://osf.io/preprints/psyarxiv/ajvg2. This work has been funded by Estonian Research Agency's personal research funding start-up grants PSG656 and PSG759, awarded to Uku Vainik, and Estonian Research Agency's grants PRG2190, awarded to René Mõttus, and PRG1291. The authors thank Artjom Rushanov and Yavor Dragostinov for their valuable feedback on an earlier version of this article.

Kätlin Anni played a lead role in conceptualization and methodology and an equal role in formal analysis and writing–original draft. Uku Vainik played a lead role in data curation and resources, a supporting role in conceptualization, and an equal role in investigation and writing–review and editing. René Mõttus played an equal role in formal analysis, investigation, methodology, and writing–original draft.
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25 occupational groups (Törnroos et al., 2019), while the other provided the Big Five mean scores for over 360 occupations (Wolfram, 2023). But for several reasons, these studies only constitute a start to the process of comprehensively and rigorously mapping occupational differences in personality traits. Here, we advance this research in multiple ways.

Limitations of Existing Work

Due to the variety of jobs that people can hold, studies on occupational differences require large samples to sample these jobs, and such studies can usually only accommodate minimalist personality assessments. Accordingly, Törnroos et al. (2019) and Wolfram (2023) used only three items to assess each broad and multifaceted Big Five domain, limiting the findings' reliability and generalizability (McCrae, 2015). The Big Five are not traits per se but broad and multifaceted domains that summarize many traits (Bainbridge et al., 2022; Goldberg, 1995), so it is impossible to achieve a full and balanced representation of them with only three items (McCrae & Mõttus, 2019). In Wolfram (2023), for example, only the anxiety aspect of neuroticism and the sociability aspect of extraversion were assessed (Lang et al., 2011), whereas both domains encompass numerous other traits such as depression, need for acceptance, dependence, social sensitivity, lack of self-efficacy and impulsiveness for neuroticism, and warmth, vigor, positivity, assertiveness, and adventurousness for extraversion (e.g., Irwing et al., 2024). Using such limited measures risks confusing broad constructs with their narrow assessments.

Moreover, both of these large studies explored occupational differences in the same sociocultural context, Britain, so their findings' generalizability to other populations requires further assessment. So, even if Wolfram (2023) and Törnroos et al. (2019) were methodologically perfect studies, it would be premature to assume that their findings accurately describe how people vary with occupations elsewhere in the world, say, Northern America, Argentina, or Estonia, and that these findings could be used for candidate selection, job counseling, or coaching in these regions. For example, in some societies, people may be comparatively more likely to choose occupations based on family traditions rather than their personal traits, reducing occupational personality differences; in contrast, in societies with particularly dynamic labor markets and/or extensive career counseling, occupational personality differences may be larger. Moreover, the traits valued at particular jobs may vary with societies. However, to the extent that occupational personality differences are replicated in cultures beyond Britain, their further generalizability becomes more plausible.

Another major limitation of the past studies is their reliance on a single trait assessment method. In addition to self-reported traits, informant reports can provide unique insights, particularly in the context of organizational psychology (Connelly et al., 2022; Connelly & McAbee, 2024; Connelly & Ones, 2010) and consistently with the trait–reputation–identity model (McAbee & Connelly, 2016) and socioanalytic theory (Hogan & Blickle, 2013). Method-specific variance constitutes a large fraction of the assessed trait score variance (McCrae & Mõttus, 2019) and could influence observed trait differences between occupations. For decades, many researchers (e.g., Connelly & Ones, 2010; Hofstee, 1994; McCrae et al., 1998; Schmidt & Hunter, 1996; Vazire, 2006) have emphasized that assessing latent constructs like personality traits with a single method, self-reports, can result in misleading conclusions. Yet, this is rarely done in personality psychology generally and occupational personality research specifically, likely because collecting multi-method data is considered difficult.

For example, people's self-reports, representing both their "true traits" and "identity," predict occupational performance worse than informants' ratings, which represent a combination of the true traits and "reputation" (Connelly et al., 2022; Connelly & Ones, 2010; McAbee & Connelly, 2016; Oh et al., 2011). This may be because job performance is often assessed by other people, both in real life (e.g., for task allocation or salary decisions) and research, and reputation may directly matter for these assessments. Likewise, career progression (e.g., hiring and promotion) may be influenced by people's reputation besides their identity because career-relevant decisions are often made by other people (Hogan & Shelton, 1998), implying that informant reports may better capture occupational differences. If so, job counseling and coaching may benefit from the use of peer reports besides or even instead of commonly used self-reports. In contrast, it is possible that some systematic assessment biases, such as socially desirable responding, vary with occupational categories (e.g., incumbents of jobs most directly relying on impression management may be particularly prone to provide socially desirable responses in personality surveys), potentially leading to inflated occupational differences according to self-reports. On the other hand, choosing occupational fields may be uniquely based on people's identity, in addition to their true traits. So, to the extent that self-selection into different jobs is a driver of occupational personality differences, these may also be larger according to self-reports. Therefore, the best trait assessment method in occupational differences research remains an open question.

Furthermore, personality traits are organized hierarchically. Although the Big Five domains efficiently summarize a substantial proportion of the personality trait space, they leave plenty unaccounted for (Mõttus et al., 2020). For example, Irwing et al. (2024) showed that there are at least 70 distinct personality facets, and there may be many more single-item nuances—stable and measurable traits in their own right that currently constitute the fundamental units of trait assessment (Mõttus et al., 2019)—within/beyond them (Condon et al., 2020). The facets and nuances often vary more across human groups, such as age (Mõttus & Rozgonjuk, 2021), gender (Hofmann et al., 2023), and nationality (Achaa-Amankwaa et al., 2021), and typically account for more variance in various life outcomes than domains (e.g., Seeboth & Mõttus, 2018; Stewart et al., 2022). Therefore, it is reasonable to expect that occupational differences may also be more pronounced in certain narrower traits than in the Big Five domains and that these narrow traits may prove particularly useful for matching people and jobs, for example. There is already evidence that nuances help to differentiate higher and lower performing employees better than the Big Five domains (Speer et al., 2022). Importantly, the question is not about which level of assessment provides the one and only correct way to represent occupational differences. Instead, multiple levels of assessment can be used at the same time, providing parallel findings that can be used depending on the purpose at hand (Mõttus et al., 2020). Sometimes, simpler domains-based findings may be useful (e.g., in narrative job counseling or coaching), while often more detailed nuances-based findings may provide the most value (e.g., for algorithmic job-matching tools). So far, however, occupational differences in nuance-level personality traits have not been explored, never mind compared to those in the Big Five.

Given these multiple limitations of past research, our current understanding of the full extent, details, robustness, and generalizability of personality traits' cross-occupational variation remains scant, even though this knowledge is crucial for (a) helping individuals find the most suitable jobs and (b) recruiters the most suitable candidates, and (c) understanding the traits' life-course consequences, among other things. Moreover, besides advancing science and assisting public services, comprehensive, methodologically rigorous, and published information about occupational variations in personality traits could lower the entry barriers for companies seeking to offer personality-based and empirically informed selection or other consultancy services, freeing them from the need to collect large data sets for occupation-specific trait norms.

Theoretical and Empirical Background

People Choose Jobs

Holland (1959, 1997) proposed six interest-based categories (realistic, investigative, social, conventional, enterprising, and artistic, referred to by the acronym RIASEC) to characterize both individuals and occupations, suggesting that congruence between them (person–job fit) contributes to a successful career choice. He proposed that people working in person-congruent occupations often enjoy their work more than those at jobs with characteristics that do not match theirs, being better-performing and more motivated, successful, and committed (Holland, 1997). Supporting this hypothesis, person–job fit is often associated with higher satisfaction, more persistence, and better performance, among other positive outcomes (Ghetta et al., 2020; Hoff et al., 2020; Kristof-Brown et al., 2005; Nye et al., 2017; Su, 2020; Van Iddekinge et al., 2011).

Holland's theory also postulates personality traits as important factors involved in occupational interests and, thereby, career choices (Holland, 1997). Indeed, a recent meta-analysis reported small to moderate ($r = -.08$ to .36) correlations between the RIASEC job interests and the Big Five personality domains (Hurtado Rúa et al., 2019), with the highest correlations between the openness and extraversion personality domains and artistic and enterprising interests, respectively, $r = .36$ and .27. However, most studies have assessed both the RIASEC interests and personality traits using self-report questionnaires rather than people's actual job titles, introducing possible shared method biases. Although a few studies have had access to actual job titles (e.g., Judge et al., 1999; Woods & Hampson, 2010), mapping these into the RIASEC framework and then relating the results with personality traits has only covered a limited range of occupations yet (Deng et al., 2007).

Likewise, the attraction–selection–attrition (ASA) model addresses the fit between individuals and their work environments (B. Schneider, 1987). According to this model, individuals are attracted to organizations with prevalent values similar to theirs, organizations select workers who are similar to the incumbents, and those who do not fit in with the organization tend (to be made) to leave. Given the links between values and personality traits (Parks-Leduc et al., 2015), the ASA model also pertains to personality more broadly, and while it conceptualizes fit at the organizational level, organizational and occupational differences are bound to overlap because different jobs are common in different organizations. Hence, the ASA model also implies personality trait differences across occupations.

Similarly, the trait activation theory (Tett & Burnett, 2003) addresses interactions between personality and work environments. It posits that personality traits are expected to manifest differently across specific contexts and situations, with traits leading to varying outcomes based on their fit with job demands and perceptions of that fit. Individuals in contexts/situations that align with their typical trait levels are likely to recognize the advantages of their traits in those contexts/situations (Tett et al., 2021). As a result, individuals' personality traits may differ across job types due to varying trait-relevant situations.

People Are Chosen for Jobs

Interests and values may not be the only mechanisms that lead to occupational stratification in personality traits. Personality traits also come with different social, emotional, and behavioral skills (Soto et al., 2022) that occupations may require to different degrees. Therefore, people with higher levels of certain skills and associated traits are more likely to be selected for and retained at the jobs requiring these skills. For example, many of those interested in managerial roles may not end up in these roles due to lacking any number of skills typically expected of leaders. Often, personality trait assessments are explicitly used in the candidate selection processes. In fact, this is a growing multibillion dollar business field, offering one of the most direct commercial applications of personality research.

Moreover, certain personality traits tend to go with higher performance in most jobs, especially those in the conscientiousness or extraversion domains but also the domains of emotional stability, openness, and agreeableness (Judge et al., 2013; Wilmot & Ones, 2021). Because more prestigious jobs may often attract more applicants and can therefore afford to be more selective regarding performance-related traits, this may contribute to typical personality trait levels varying across jobs.

Jobs May Change People

Roberts (2006) extended the ASA model to accommodate personality change, reviewing evidence to support trait changes in response to occupational characteristics (socialization) available at that time. The totality of evidence accumulated since then suggests that specific life experiences of any kind usually have only modest effects on personality traits, at least in ways that are similar across people (Bühler et al., 2023), making work experiences' large and systematic roles in personality change unlikely. Yet, personality trait change is common (Mõttus, 2022), and job-related experiences that vary across occupations may play *some* role in it (Holman & Hughes, 2021; Wu, 2016; Zheng et al., 2023).

Perhaps most plausibly, job-related experience may accentuate the traits that contributed to people ending up in these jobs in the first place, consistently with the corresponsive principle of personality development (Le et al., 2014; Roberts et al., 2003). For example, being in leadership, sales, or care positions may amplify the traits typically required to choose and be chosen for these positions; sometimes, this is explicitly intended with coaching support (Mccormick & Burch, 2008). This idea is also consistent with the demands-affordances transactional model (Woods et al., 2019) and the Triggering Situations, Expectancy, States/State Expressions, and Reactions framework (Wrzus & Roberts, 2017), which both describe trait changes resulting from transactions between personality traits and persistent situations. Hence, both the selection and socialization effects may similarly contribute to average trait differences between occupations.

Which Traits May Vary With Which Occupations?

As it is impractical to articulate hypotheses for the mean levels of every trait for every occupation, we describe several broad expectations for personality trait differences between occupational groups, directly and indirectly informed by relevant past work. Primarily, we focused on the five-factor model (McCrae & John, 1992), or the Big Five (Goldberg, 1993), which is currently the most widely used descriptive personality trait model. As it has also been utilized in comparable studies (e.g., Törnroos et al., 2019; Wolfram, 2023), we could directly use their results to derive hypotheses and cross-validate our results against their findings (Table 1).

Specifically, Törnroos et al. (2019) analyzed personality traits among 25 occupations using the submajor groups of the SOC2000 classification of occupations ($N \sim 23{,}000$), while Wolfram (2023) compared the Big Five personality traits across 360 occupations using the SOC2010 classification at the more fine-grained unit group level ($N \sim 28{,}700$); both studies used a very brief personality test and British samples. The findings revealed cross-occupation variations in all Big Five domains, particularly in openness. For example, creative and research roles showed the highest openness scores, while machine operative and elementary occupations showed the lowest scores. Diverse managers had comparatively high average scores in extraversion and lower scores in neuroticism. In contrast, occupations related to science and technology had the lowest average scores in extraversion, while creative jobs scored the highest in neuroticism. Conscientiousness tended to be the highest among health professionals or assistants, various managers, and skilled tradespeople but lower in sales and customer service occupations. High agreeableness was observed in personal and health care, customer service, and religious professions, while it averaged lower in machine operation, mechanical–electrical engineering, and construction-related jobs.

Moreover, some studies have analyzed Big Five traits across occupations in Germany (John & Thomsen, 2014; Nieken & Störmer, 2010) and Australia (Junankar et al., 2009; Wells et al., 2016), but focusing on 6–8 broad occupational groups and hence offering limited granularity. For example, manual workers, operators, and craftspeople scored lower in openness, while those with higher qualifications (e.g., technicians, managers, professionals) scored higher, on average. Likewise, managers displayed a pattern of higher extraversion and conscientiousness and lower neuroticism (Nieken & Störmer, 2010; Wells et al., 2016), while service workers tended to have higher extraversion scores (John & Thomsen, 2014; Nieken & Störmer, 2010). Research focusing on specific occupations has revealed similar trends. For instance, in Lounsbury et al. (2016), managers tended to have higher levels of extraversion, conscientiousness, openness, and agreeableness and lower levels of neuroticism compared to nonmanagers. Likewise, scientists were characterized by higher openness and lower extraversion (Lounsbury et al., 2012), while religious professionals,

Table 1
*The Expectations for the Associations of the Big Five Personality Domains With Specific (Highest and Lowest Scoring) Occupations and O*NET Work Styles*

Big Five domain	Hypothesized association with occupation and O*NET work style
Extraversion	Highest scores: diverse managers, business and public service professionals, diverse salespeople. Lowest scores: science and technology professionals, several types of ICT professionals, engineers, and engineering technicians. Work styles: highest correlations with social orientation, leadership.
Openness	Highest scores: culture-, media-, and sports-related occupations, teaching and research professionals, and science and technology professionals. Lowest scores: diverse machine drivers and operatives, elementary occupations, cleaners, and clerks. Work styles: highest correlations with analytical thinking, innovation, adaptability, independence, leadership.
Neuroticism	Highest scores: culture-, media-, and sports-related occupations, administrative occupations, teaching and research professionals, and clerks. Lowest scores: skilled construction and building workers, health professionals, managers, and mechanics. Work styles: lowest (negative) correlations with self-control, stress tolerance, adaptability/flexibility, integrity.
Conscientiousness	Highest scores: health professionals/assistants, diverse skilled trades occupations, managers in various areas. Lowest scores: sales and customer service occupations, elementary administration occupations, artistic/creative occupations. Work styles: highest correlations with dependability, initiative, persistence, achievement/effort, attention to detail, independence, leadership, integrity.
Agreeableness	Highest scores: care and service occupations, teaching and research professionals, religious professionals. Lowest scores: process, plant, and machine operatives, diverse managers, mechanical and electrical engineers, construction/building workers. Work styles: highest correlations with concern for others, cooperation, social orientation, integrity.

Note. Listed occupations are based on the results of Törnroos et al. (2019) and Wolfram (2023). Hypotheses about O*NET are based on Sackett and Walmsley (2014) and Hough and Ones (2001). O*NET = Occupational Information Network database; ICT = information and communications technology.

such as priests, tended to have higher agreeableness but lower scores in extraversion and openness (Cerasa et al., 2016).

Expectations for our findings based on these earlier results are summarized in Table 1. But besides directly comparable past work, expectations for occupations' average personality trait profiles can also be indirectly informed by studies that associate the RIASEC interest types with Big Five traits (Hurtado Rúa et al., 2019). With extraversion most strongly associated with enterprising and social interest dimensions, higher extraversion scores might characterize managers, marketing professionals, and salespeople, as well as teachers, social workers, and community health workers. As conscientiousness partly aligns with conventional interests, its high scores could characterize detail-oriented roles such as office clerks, analysts, and accounting and financial specialists. Agreeableness' association with social interests suggests higher mean scores in roles involving helping people, such as teaching and social work. Openness correlates with artistic and investigative interests, suggesting higher mean scores for creative fields like art, design, and research. All these expectations are generally in line with past research comparing occupations in the Big Five, especially on extraversion, agreeableness, and openness (Table 1). With neuroticism not systematically tracking occupational interests, it may contribute less to interests-based job selection; however, since high neuroticism may often be an obstacle in high-stress occupations, it could still vary with jobs for other reasons. This leads us to consider jobs' prototypical work styles.

We also considered the Occupational Information Network database (O*NET; Peterson et al., 2001), developed by the U.S. Department of Labor, which covers thousands of occupations, is linked with several other databases, and encompasses a wide array of data about occupations, including job requirements, descriptions, and expected worker attributes. These include variables sourced from various personality-like scales, collectively referred to as work styles (Borman et al., 1999). The O*NET work styles are organized into seven higher order constructs—achievement orientation, social influence, interpersonal orientation, adjustment, conscientiousness, independence, and practical intelligence—and 16 subordinate constructs, such as persistence, leadership orientation, self-control, and dependability, among others. With the O*NET focusing on job analysis, the constructs' assessments were based on ratings of their importance on the job. Among the O*NET's various limitations (Handel, 2016), however, the work styles' ratings were provided by a modestly sized mix of incumbents or occupational experts (typically, N = 20–40, Mdn = 24) who completed a short 16-item questionnaire. So, besides possible issues with reliability and validity, the work style ratings were meant to reflect the characteristics *expected to be* associated with better job performance and *not the actual* traits of the incumbents, never mind the personality traits typically used to summarize differences among people, such as the Big Five. Hence, reliably mapping commonly studied personality traits among incumbents can provide valuable information that could eventually be integrated with the job analysis data in the O*NET database.

At this point, we incorporated the work style ratings into our expectations for actually existing trait differences between occupational groups, among other information. For example, based on the O*NET work style ratings and their expected alignment with the Big Five (Hough & Ones, 2001; Sackett & Walmsley, 2014), we expected that occupations requiring analytical thinking, such as science and research jobs, have higher mean scores of openness, and occupations requiring leadership abilities, like managerial roles, have higher mean scores of extraversion. For more expectations, see Table 1.

The Differences' Expected Magnitudes

Although researchers often focus on which variables "significantly" differ between groups (e.g., salespeople may be significantly more extraverted than accountants, on average), the *overall magnitude of occupational differences* in personality traits is also important. For example, the larger the differences are overall, the stronger the empirical case for using personality traits in career counseling, coaching, and applicant selection in the first place. Likewise, larger occupational differences provide a stronger empirical basis for claims of the "power of personality" in shaping life outcomes (Roberts et al., 2007).

Personality trait differences across human categories that most people do not select for themselves are typically relatively modest. For example, gender accounts for about 1%–6% of Big Five variance, on average, across studies (McCrae & Terracciano, 2005; Schmitt et al., 2008). Age (group) differences may be only somewhat larger (Bleidorn et al., 2022), while national differences are typically even smaller (Allik et al., 2017). Because people often have more control over their occupational choices than their gender, age, or nationality, and because they may be selected for jobs partly based on their personality-related skills, personality trait differences across occupations may be larger, especially if properly assessed.

Yet, the evidence is unclear. For example, while occupations accounted for 7%–10% of Big Five variance in Wolfram (2023), only 1%–4% of Big Five variance could be ascribed to the occupations in Törnroos et al. (2019). It is unclear whether these between-study differences are substantive or due to methodological discrepancies: Wolfram relied on a broader range of occupations and adjusted trait scores based on external-to-personality information (O*NET's job characteristics), whereas Törnroos et al. controlled for age and gender and did not include external information. Either way, both studies relied on minimalist personality assessments, whereas accurately estimating occupational differences requires not only a well-characterized set of occupations but also comprehensively and reliably assessed personality traits: Any given miniscale may happen to capture the most job-relevant aspects of the Big Five personality domain it is assessing, but it may also miss them.

Based on the study most similar to ours (Wolfram, 2023) but also because our trait assessment was more comprehensive, we expected that a broad range of occupations may account for about 10% of Big Five domains' variance, assessed thoroughly in the general population for a broad range of occupations. Given that various personality nuances usually vary more between groups and explain more variance in life outcomes than domains, we expected occupational differences to be larger in at least some nuances. We were open to whether the magnitude of occupational differences would be smaller (e.g., due to hiring and promotion decisions based on reputation) or larger (e.g., identity uniquely contributing to career choice or self-report biases affecting occupational trait scores) in self-reports versus informant reports, or whether the two assessment methods would reveal similar effect sizes, thus supporting the robustness of occupational personality trait differences.

Some Jobs May Be More Personality-Homogeneous Than Others

Besides mean trait scores, groups can also differ in how homogeneous they are in these scores (Mõttus, Soto, &

Slobodskaya, 2017; for cross-occupation differences in interests' variance, see Nye et al., 2018). For example, it is already well established that (more prestigious) occupations with higher mean psychometric intelligence levels typically vary less in these scores than occupations with lower mean intelligence levels, hence being cognitively more homogeneous (Harrell & Harrell, 1945; Jensen, 1980; Wolfram, 2023). This can be interpreted as high cognitive ability often being a necessary but not sufficient condition for landing a prestigious job. Although less studied, there is no reason that the same could not apply to personality traits: Those trait levels that generally help with job performance, such as high emotional stability (low neuroticism), extraversion, openness, agreeableness, and conscientiousness (Judge et al., 2013), may be beneficial but not sufficient for higher performance and typically more prestigious jobs. Therefore, certain jobs can afford to be more selective for people with these traits, potentially leading to both higher means and lower variances among their incumbents. Furthermore, the idea of "situation strength" (Meyer et al., 2010; Sitzmann et al., 2019) suggests that more structured and demanding jobs may limit the scope for personality expression, contributing to the observed homogeneity in traits among incumbents.

This question was empirically addressed by Wolfram (2023), but the evidence was mixed: The correlations between occupation's mean personality trait scores and the traits' standard deviations (*SD*s) within the occupations were significant for all traits except agreeableness but in the opposite direction to what we would expect for extraversion. However, as noted by the author, estimating this relation was complicated by the ceiling problem, whereby the trait's variance was (artificially) more restricted in occupations with more extreme mean scores, especially because the scores were based on only three items and hence had highly restricted variance to start with.[1] Owing to a more comprehensive assessment approach, our data enabled testing this hypothesis more powerfully. Specifically, each Big Five domain was assessed as the weighted composite of 60 items, necessitating a normal-like distribution (due to the central limit theorem) with many possible trait levels and ample room for variance even within groups with a range of different mean levels (additional online material Figure S2 at https://osf.io/5eaxv).

Objectives and Contributions of This Study

We compared 263 occupations in comprehensively assessed personality traits in a large population sample of Estonians, estimating the overall variance in the traits explained by the occupations and ranking the occupations in them. Our sample ($N = 68{,}540$) was much larger than those of previous studies and covered nearly 7% of the Estonian adult population, allowing us to systematically compare both common and rarer occupations; addressing a wide range of occupations, large samples are vital in this research.

Besides the self-reported Big Five personality domains, we compared the occupations in a range of narrower traits, personality nuances, that showed occupational differences at least equal to the typical association strength in psychology ($r \approx .20$, $\eta^2 = .04$), which is deemed the threshold for medium effects with potential practical and explanatory use (Funder & Ozer, 2019). Many have argued that the Big Five may be too broad to understand or predict work-related criteria (Hough & Oswald, 2005; Paunonen et al., 1999; R. Schneider et al., 1996; Tett & Burnett, 2003), but systematic research on mapping occupational differences in narrower traits has been even more limited than the Big Five-based work. For cross-validation, we also assessed occupational differences in informant-reported personality traits (reputation) and directly compared our findings to the most comparable existing evidence (Wolfram, 2023). Moreover, for a better understanding of the similarities and differences between distinct approaches to describing psychological differences between occupations, we correlated our occupational rankings with the O*NET work styles.

Furthermore, we mapped occupations based on their incumbents' average trait profiles to see how they are organized in psychological similarity and to what extent this psychological organization complies with how the jobs are hierarchically classified based on their tasks by the International Labour Organization. To make the occupational personality profiles easily accessible to scientists, practitioners, and the public, we also developed an interactive web application (https://apps.psych.ut.ee/JobProfiles/). Finally, we tested the idea that occupations with higher mean scores in emotional stability, extraversion, openness, agreeableness, and conscientiousness—that is, trait levels typically associated with higher job performance (Judge et al., 2013)—are more homogeneous in their trait scores than occupations with lower mean levels in these traits. This would suggest that person–environment fit is not uniformly distributed across occupations (e.g., some jobs are more selective) and that personality-based job-matching may be particularly useful for higher performing jobs.

Method

Transparency and Openness

We adhered to the *Journal of Applied Psychology* methodological checklist, including a description of our sampling plan, all data exclusions, manipulations, and measures in the study. The data cannot be publicly shared, as they are part of an extensive ongoing biobank study. However, researchers can apply for access to the data (https://genomics.ut.ee/en/content/estonian-biobank). Statistical analyses were carried out with R language, Version 4.3.1 (R Core Team, 2023). The R code is available at https://osf.io/m9sw3/. Analyses were not preregistered.

Sample

Participants were members ("gene donors") of the Estonian Biobank (EstBB), a population sample of approximately 200,000 adults comprising about 20% of Estonian adult residents or past residents currently living abroad (https://genomics.ut.ee/en/content/estonian-biobank). The personality ratings and job titles used in this study were collected through an online EstBB Personality Study (PS21) survey between November 2021 and April 2022, with email invitations sent to 182,405 gene donors (Vaht et al., 2024). To encourage participation, the study was advertised on national radio,

[1] For example, when items are responded to using a 1–7 Likert-type scale, the sum-scores of a three-item scale can vary from 3 to 21, having 19 possible values. However, even with improbable uniform distributions of item responses, most scores would vary from 7 to 17, whereas with more plausible normal-like distributions, most responses would vary between 8 and 16, hence taking only nine possible values. Skewed distributions would restrict the variance even more.

television, newspapers and magazines, and on social media; participants were also offered feedback on their Big Five personality trait scores. Optionally, participants were asked to provide an email of another person (informant) who could complete the third-person form of the personality items about them. After reading information about the study, participants (and their informants, where applicable) electronically signed a consent form. Participants could choose to participate in either Estonian or Russian, but we only used data provided in Estonian to not confound language differences with group differences. After removing respondents with more than 10 missing personality questionnaire responses and no occupational data, we were left with 68,540 participants (sex assigned at birth: 48,231 women, 20,309 men; age: range from 18 to 102; $M = 47.9$, $Mdn = 47.0$, $SD = 14.6$), 19,989 of whom were also rated by an informant with up to 10 missing responses (sex assigned at birth: 13,616 women, 6,373 men; age: range from 18 to 93; $M = 45.5$, $Mdn = 44.0$, $SD = 13.6$). The informants were usually partners or spouses (56%), children/grandchildren (14%), friends (14%), parents/grandparents (7%), or other relatives (8%). The activities of the EstBB are regulated by the Human Genes Research Act, which was adopted in 2000 specifically for the operations of the EstBB. Individual-level data analysis in the EstBB PS21 was carried out under ethical approval 1.1-12/626 (13.04.2020) from the Estonian Committee on Bioethics and Human Research (Estonian Ministry of Social Affairs), using data according to release application 3-10/GI/11571 from the EstBB. As this study was part of a broader data collection effort (Vaht et al., 2024), parts of the data set have been previously analyzed in Mõttus et al. (2024) and Arumäe et al. (2024).

Measures

Personality Traits

In the EstBB PS21, we decided to assess participants' personality domains and nuances more comprehensively and orthogonally than it is possible using existing Big Five measures; the full rationale for our approach is described in the additional online material (see folder "The Reliability and Validity of the Big Five Scores in the 100-NP," https://osf.io/m9sw3/). For this, participants and their informants completed a 198-item pool, 100 Nuances of Personality (100-NP), designed to cover numerous personality traits with reduced redundancy. It captures trait content associated with facets and domains assessed in standard Big Few measures and some traits typically not covered by these (e.g., competition, envy, humor, sexuality, spirituality, and the "Dark Triad" traits). Based on the rationale described in Condon et al. (2020), the 100-NP items were iteratively selected from larger item pools such as the International Personality Item Pool (Goldberg, 1999) and Synthetic Aperture Personality Assessment (Condon & Revelle, 2016) for their diverse content and retained if they (a) had acceptable test–retest reliability, variance, and cross-rater agreement and (b) were not excessive redundant with other items, except some more highly correlated items to assess acquiescent responding and provide two items of apparently less reliably assessable traits (e.g., impulsiveness). Participants responded using a 6-point Likert-type scale, ranging from *completely inaccurate* to *completely accurate*. A full description of the 100-NP's development can be found in Henry and Mõttus (2023), and items can be found in the additional online material on the Open Science Framework (OSF; https://osf.io/tcfgz/).

We calculated participants' Big Five scores based on 60 items. We selected these by (a) averaging standardized self-ratings and informant ratings of 20,886 participants who had no more than 10 missing responses for personality items (replacing remaining missing responses with the median); (b) dropping the item with less variance from each pair correlating above .50 and dropping items with no correlation with other items at least .30 (to avoid redundancy as well as isolated items); (c) running the principal component analysis on the remaining 119 items, extracting five varimax-rotated components and retaining 12 highest-loading items for each component; (d) rerunning principal component analysis with the remaining 60 items and using the resulting loading matrix to calculate participants' Big Five scores in self-reports and, when available, informant reports. This procedure ensured that Big Five scores were relatively orthogonal (absolute intercorrelations between .02 and .11, $Mdn = .05$, in self-reports and 0 and .15, $Mdn = .04$, in informant reports), unlike those of most Big Five questionnaires (van der Linden, 2010); similarly calculated in self-reports and informant reports; and based on sufficiently diverse item content. The components' item loadings clearly resembled a typical Big Five content (additional online material Table S1 at https://osf.io/y735x). The five components explained 37%, 42%, and 44% of items' variance in self, informant, and combined ratings, respectively. As one of the most straightforward validity criteria, the scores' cross-rater correlations were .55, .59, .50, .45, and .51, respectively, for neuroticism, extraversion, openness, agreeableness, and conscientiousness, well above typical estimates (Connelly & Ones, 2010).

In the additional online material at https://osf.io/m9sw3/, we provide a comprehensive psychometric evaluation of the 100-NP Big Five scales based on these and various additional data. In short, the scales demonstrated high test–retest reliability ($r = .85$–$.88$) and a robust Big Five-themed principal component structure that replicated across samples and languages. We demonstrate their convergent validity through high intercorrelations with other Big Five measures, including the 240-item NEO Personality Inventory–3 (McCrae & Costa, 2010) and 60-item Short Five (Konstabel et al., 2012), Big Five Inventory–2 (BFI-2; Soto & John, 2017), and International Personality Item Pool–NEO (Maples-Keller et al., 2017). The scores' discriminant validity was supported by dramatically lower interscale correlations than those of these other Big Five measures. Supporting the 100-NP's comprehensiveness, its scales always captured more variance in those of other equally long Big Five measures in multivariate analyses, and they captured equal amounts of variance with the Big Five scales of the four times longer NEO-Personality Inventory–3. Furthermore, the scales showed meaningful correlations with a range of other psychological constructs known to be related to the Big Five. We believe this combination of evidence strongly supports the superior validity of the component scores as measures of the Big Five domains.

Occupations

Participants answered an open-answer question: "Please write the title of your main occupation (right now or before discontinuing the work)?" These self-reported answers were renamed and regrouped as needed for a more straightforward coding procedure based on the latest International Standard Classification of Occupations–08 (ISCO-08; International Labour Office, 2012) Estonian version (available at https://web.archive.org/web/20240614090348/https://klassifikaatorid.stat.ee/item/stat.ee/b8fdb2b9-8269-41ca-b29e-5454df555147/14). The first and third authors used the quantitative discourse analysis R package qdap to rename self-reported answers besides "manually" rephrasing (where the automatic procedure failed) and organizing the responses, to correct the spelling mistakes, and to combine idiosyncratic job titles with somewhat more common titles that could be later organized according to the ISCO-08 classification. Since some answers contained multiple occupational titles, we selected the first for grouping and renaming; occasionally, we considered the second title when the first was too broad or generic. After renaming highly idiosyncratic or misspelled titles, we grouped them according to the ISCO-08 Estonian version. The ISCO classification follows a hierarchical framework with several levels of categorization: major groups with 1-digit codes (1d groups), submajor groups with 2-digit codes (2d groups), minor groups with 3-digit codes (3d groups), and unit groups with 4-digit codes (4d groups). The unit group (4d) level allows all jobs to be classified into 436 groups that can be aggregated into 130 minor groups (3d), 43 submajor groups (3d), and 10 major groups (1d). For example, at the broadest level are the major groups, such as "2—professionals," representing a wide category of jobs characterized by broadly similar skill levels and qualifications. Within these are the submajor groups, such as "25—information and communications technology professionals," which split further into minor groups, such as "251—software and applications developers and analysts," offering more detailed divisions within the major and submajor groups, respectively. The most granular level is the unit groups, such as "2,512—software developers," describing individual occupations or groups of presumably very similar occupations in terms of skill level and specialization (International Labour Office, 2012).

All steps of renaming and coding can be retraced in the publicly available R code and job title correspondence spreadsheets (one for converting 7,600 idiosyncratic titles into more common titles, which cannot be made publicly available to protect participant privacy; another for converting job titles into ISCO groupings, which is publicly available). The reproducible R-code for the renaming and grouping of the titles enabled us to do several quality analyses and cross-checking and subsequent modifications without separately coding all the answers. Specifically, over several months, the first and third authors actively engaged in renaming individual occupations and developing the grouping scheme, having extensive back-and-forth discussions about both idiosyncratic job titles that required renaming and the specific steps for categorizing job titles, cross-checking each other's work, and further discussing any discrepancies until they achieved a consensus.

We aimed to assign each job title to a 4d ISCO (unit) group. However, some job titles (e.g., "head of department," "team leader," "analyst," "consultant," "coordinator") were too generic to be assigned to an existing 4d group. Given that many of these titles were common, we created some additional 4-digit codes based on the broader 1d or 3d groups to which the titles could belong. For example, the answer "analyst" broadly fits within the 1d category "professionals," which is denoted by the code "2." Yet, the term refers to a specific job group among professionals, albeit not enough to the granularity of an existing 2d, 3d, or 4d group. To address this nuance and distinguish it from other generic professional roles, we assigned it the code "202x." In this code, "2" denotes its affiliation with the 1d group of "professionals"; "02" is the sequence number indicating its order among the codes we created within the "professionals" category, and "x" stands for our unique identifier. For another example, the answer "education professional" can be placed under the 3d category "other teaching professionals," denoted by the code of "235." However, assigning a precise 4d code is unfeasible without more detailed information, as there are numerous professions within that 3d group. To differentiate it from other professions under that category, we allocated the unique code "235x" to this group. In that code, the "235" represents its 3d group, and "x" is a marker that distinguishes this code from other standard ISCO-based codes. All 26 self-generated codes and the specific job titles to which they correspond are shown in additional online material Table S2 at https://osf.io/y735x. For comparison, the additional online material at https://osf.io/m9sw3/ also contains a subset of analyses conducted without these self-generated occupational codes, and our interactive online application allows filtering out those job titles.

We managed to code 68,540 out of 69,351 individual responses that met our specified criteria (personality questionnaire completed in Estonian with no more than 10 missing items). Most of the uncoded responses indicated unemployment or retirement without listing prior occupations or were restricted to nonoccupational terms like "student" or "pupil." Additionally, some uncoded responses were too ambiguous, referring to a general field (e.g., "IT," "finance," "development") or a specific organization without specifying a particular job.

We compared the proportions of occupational groups in our sample to those of the Estonian population in general (see additional online material Table S10 at https://osf.io/y735x). People in managerial and professional occupations (ISCO 1d codes 1 and 2) were overrepresented in our sample, while craft and related trades workers (ISCO 1d group 7), machine operators and assemblers (ISCO 1d group 8), and elementary occupations (ISCO 1d group 9) were underrepresented. The participant proportions in other occupational categories, such as the armed forces (ISCO 1d group 0), technicians and associate professionals (ISCO 1d group 3), clerical support workers (ISCO 1d group 4), service and sales workers (ISCO 1d group 5), and those in agriculture, forestry, and fishery (ISCO 1d group 6), closely mirrored the demographic composition of the Estonian population (Statistics Estonia, n.d.).

Data Analysis

We first residualized personality traits (domains, items) for age and gender and converted them to T-scores ($M = 50$, $SD = 10$), although we also report estimates for unresidualized traits for reference. We dropped participants from the 4d occupational groups with less than 25 participants (83 groups, $N = 938$ self-reports; 156 groups, $N = 1,477$ informant reports) and randomly sampled 1,000 participants from groups with over 1,000 participants (12 groups, dropping $N = 8,575$ self-reports; one group, dropping $N = 16$ informant reports) to avoid the largest groups' dominance in the results (e.g., analysis of variance). This left us with $k = 263$ occupational groups and a total sample size of 59,027 with self-reported traits and $k = 176$ occupational groups comprising 18,496 participants for analyses involving informant-reported traits (sample sizes for all groups are shown in additional online material Tables S2 and S3 at https://osf.io/y735x).

The Strength of Job-Trait Relationships

To quantify the proportion of variance in personality traits explained by jobs, we calculated the eta-squared (η^2) from a series of analyses of variance with traits as dependent variables and job groups as categorical independent variables. To estimate whether narrower occupational groups (e.g., 4d) and broader "parent" groups (e.g., 3d) in the hierarchical ISCO classification varied in their typical Big Five domain scores, we calculated η^2-values for each of the four levels of job categorization (from the most specific, 4d, to the broadest, 1d).

Besides the Big Five domains, we calculated 4d groups-based η^2s for 188 individual items that did not assess life satisfaction (4), domain satisfaction (3), or traits associated with these (3; Mõttus et al., 2024). We took items with η^2s $\geq$ .04 (rounded to the second decimal, corresponding to $r = .20$, a medium effect size in psychology with potential practical significance; Funder & Ozer, 2019) forward as markers of personality nuances that could provide fine-grained information on occupational differences; to avoid redundancy, we dropped the item with lower η^2s from each item pair correlating above .50 (with typical item's reliability ~.65, this means approximately 25% or more reliable item-specific variance in each item; Henry & Mõttus, 2023). We refer to these relatively unique items as nuances.

Smoothing Means and Standard Deviations

Many less represented occupational groups can have unique and thus practically and theoretically useful personality trait profiles, but the traits' (domains, nuances) mean and variance estimates for these groups can also be unreliable due to sampling biases. We addressed this risk by balancing the unique information in these groups' (self- and informant-reported) trait scores' means and *SD*s with the higher reliability of the means and *SD*s of the larger parent groups to which the occupations belonged. To achieve this, we smoothed the means/*SD*s of 4d ISCO groups toward the means/variances of their parent groups (e.g., 3d ISCO groups) according to the rule where at the smallest possible 4d group size (i.e., 25), the two means/*SD*s would be weighted equally in the smoothed means/*SD*s, whereas with ever higher 4d groups, their weight would increase relative to the parent group. In Bayesian terms, we could think of the 4d group's means/*SD*s as data, the parent group's means/*SD*s as priors, and the resultant smoothed means/*SD*s as posteriors, so the question became about the relative weights of data over priors. Denoting the 4d group's size n and the weights ascribed to the 4d group and its parent group w_{data} and w_{prior}, respectively, $w_{\text{data}} = w_{\text{prior}}$ with $n = 25$, whereas $w_{\text{data}} > w_{\text{prior}}$ with $n > 25$. So, we set $w_{\text{prior}} = 25$ and used the Equation 1 to derive w_{data} as a function of n:

$$w_{\text{data}} = \frac{n^2}{25}. \tag{1}$$

Given this rule, with 4d groups of size $n = 50$, $w_{\text{data}} = 100$, so the relative weight of the 4d group mean/*SD* over its parent group's mean/*SD* in the smoothed mean/*SD* was $\frac{100}{100+25} = 0.80$, whereas with $n = 100$, $w_{\text{data}} = 400$ and the relative weight was $\frac{400}{400+25} = 0.94$. In other words, with 4d groups of sizes 25, 50, and 100, their means/*SD*s were moved 50%, 20%, and 6% toward their parent groups' means/*SD*s. The relative weights for other sample sizes up to $n = 200$ are shown in Figure 1. For smoothing the means and variances of the 4d groups' *T*-scores, we used the Equations 2 and 3:

$$m_{\text{posterior}} = \frac{w_{\text{prior}} \cdot m_{\text{prior}} + w_{\text{data}} \cdot m_{\text{data}}}{w_{\text{prior}} + w_{\text{data}}}, \tag{2}$$

$$\text{var}_{\text{posterior}} = \frac{w_{\text{prior}} \cdot \text{var}_{\text{prior}} + w_{\text{data}} \cdot \text{var}_{\text{data}}}{w_{\text{prior}} + w_{\text{data}}}. \tag{3}$$

The corresponding 3d group was chosen as the parent group if it had at least 100 people; otherwise, the corresponding 2d group was chosen, and if this did not contain observations for at least 100 people, the corresponding 1d group was used. To test and illustrate the effect of smoothing, we correlated the raw and smoothed means/*SD*s and visualized the relations as a function of n, using the *ggplot* and *plot_grid* functions of the ggplot2 and cowplot R packages. Group names and codes according to ISCO for 1d–3d groups are in the additional online material Tables S7–S9 at https://osf.io/y735x.

We report these smoothed means and variances for the Big Five domains and retained items for all occupations in interactive tables at https://apps.psych.ut.ee/JobProfiles/, while the smoothed means and *SD*s for all items are reported in the additional online material Tables S4 and S5 at https://osf.io/y735x for the record. The interactive tables were created with the *datatables* and *saveWidget* functions from the DT R package. For each domain, we report the means and *SD*s for the 10 highest- and lowest-scoring occupations; for nuances, we report them for the three highest- and lowest-scoring occupations to save space.

Cross-Validation

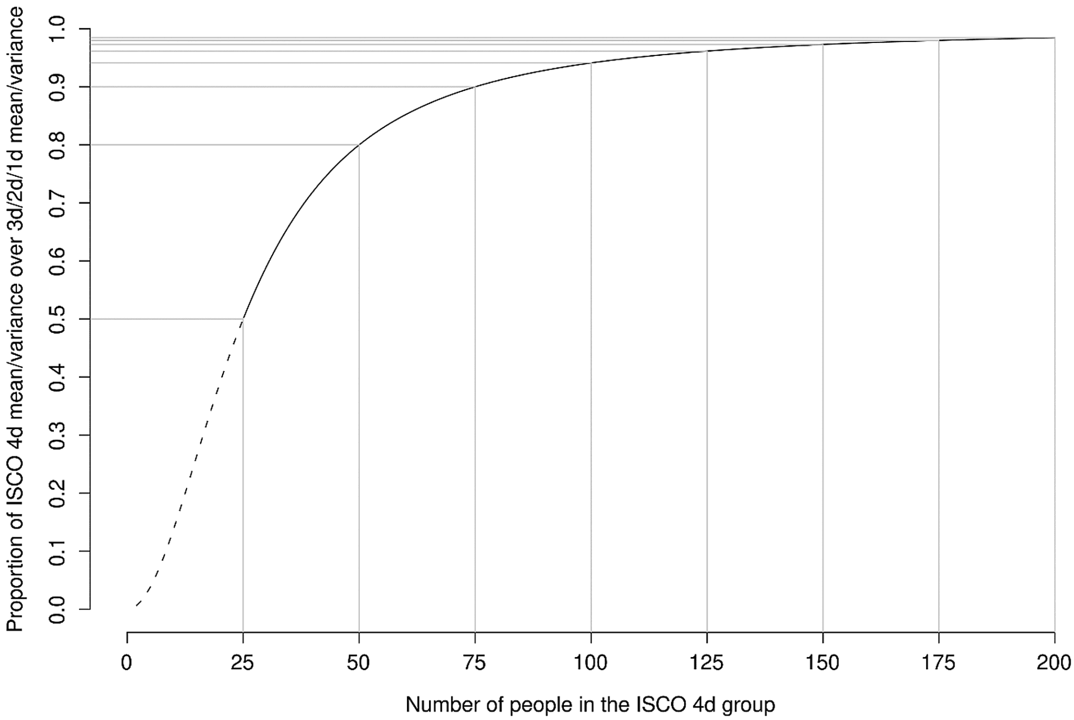
The smoothed mean trait scores were used for cross-validation, comparing the traits' (domains, nuances) rankings of the (4d) occupational groups according to self-reports and informant reports and comparing the mean self-reported domain scores to those reported by Wolfram (2023). For the former, we used two sets of self-reported scores to disentangle sampling and method variation: (a) based on all available participants and (b) based on those for whom informant reports were also available. For comparison with Wolfram (2023), we did not residualize traits for age and gender for comparability.

Correlations With O*NET Work Styles

Ratings for 16 O*NET work styles are available for a total of 873 occupations in the O*NET database. We utilized the crosswalk provided by the European Commission (available at https://esco.ec.europa.eu/en/use-esco/other-crosswalks and in the additional online material, file "ONET_ESCO crosswalk" at https://osf.io/nj3dy) to convert O*NET occupational codes into European Skills, Competences, Qualifications and Occupations codes, which are compatible with ISCO-08 4d codes. In cases where multiple O*NET jobs corresponded to a single ISCO-08 4d code, we calculated the mean work style values for that ISCO code. As a result, we were able to derive work style evaluations for 213 out of 263 occupations that were included in our main analyses. We correlated these with the age- and gender-adjusted smoothed Big Five scores.

Figure 1

Relative Weights of Smoothing for Four-Digit Group Means/Variances Based on Sample Size



Note. ISCO = International Standard Classification of Occupations.

Multidimensional Scaling

To represent multidimensional trait profiles based on domains and nuances in a two-dimensional space, we used classical multidimensional scaling (MDS) that can map the profiles' Euclidean distances with fewer dimensions, implemented in the *cmdscale* R function. To ease the interpretability of the two dimensions, using the *target.rot* function of the psych R package, we rotated them toward the Big Five domains that each correlated the most with while still aiming to keep them near-orthogonal. The results were visualized using the *ggplot* function. An interactive version of the domain-level plot is available at https://apps.psych.ut.ee/JobProfiles/, created with the *girafe* and *saveWidget* functions of the ggiraph and DT R packages.

Occupational Homogeneity

To test the hypothesis that jobs with higher mean scores of typically performance-related traits (i.e., higher emotional stability and other Big Five domains) are more homogenous in these scores, we correlated the domain's smoothed means and *SD*s across all occupations. This analysis was based on the assumptions that the 60 item-based component scores were not skewed and had sufficient variance (likely due to the central limit theorem) and the job's trait distributions were not too distant from each other (i.e., modest mean differences) to avoid ceiling and floor effects in specific job groups; if these assumptions were not met, we should have seen a pattern of both relatively low and high mean scores being associated with less variance. We show the domain scores' normal-like distributions in the additional online material Figure SM2 at https://osf.io/5eaxv and visualize the associations of the smoothed means and variances. In the additional online material Tables SM2 and SM3 at https://osf.io/y735x, we also report multiple regression results where domains' variances were predicted by both means and the groups' sizes to account for the possible confounding effect of sample sizes (e.g., smaller groups being outliers in both means and variances). We did not test this hypothesis for nuances because individual items had limited variance and were more susceptible to floor and ceiling effects.

To assess whether the associations may be explained by other performance-related factors as suggested by a reviewer, we also calculated partial correlations between occupations' trait means and *SD*s, controlling for income and Standard International Occupational Prestige Scale (SIOPS; Ganzeboom & Treiman, 1996) scores. Income was collected with an open-ended question: "What is your personal average monthly income (net, in euros)?" Responses ranging from €100 to €100,000 were log-transformed for further analysis; those higher than €100,000 were capped at this value. These income data, available for 55,643 individuals, were then averaged for each occupational group. For the non-self-generated 4d ISCO-08 codes ($k = 237$), SIOPS scores were directly derived using the DIGCLASS package, which converts ISCO-08 codes into various social class variables; for self-generated occupational codes ($k = 26$), SIOPS scores were estimated using their respective 2d parent group codes.

Software

Data analyses were carried out using R Version 4.3.1 (R Core Team, 2023). The following packages were used: tidyverse (Version 2.0.0; Wickham et al., 2019), fuzzyjoin (Version 0.1.6; Robinson, 2020), qdap (Version 2.4.6; Rinker, 2023), stringdist (Version 0.9.10; van der Loo, 2014), rempsyc (Version 0.1.6; Thériault, 2023), splitstackshape (Version 1.4.8; Mahto, 2019), ggplot2 (Version 3.4.2; Wickham, 2016), cowplot (Version 1.1.1; Wilke, 2020), DT (Version 0.28; Xie et al., 2023), psych (Version 2.3.6; Revelle, 2023), ggiraph (Version 0.8.7; Gohel & Skintzos, 2023b), flextable (Version 0.9.3; Gohel & Skintzos, 2023a), shiny (Version 1.7.5; Chang et al., 2023), DIGCLASS (Version 0.0.1; Cimentada et al., 2023), and ppcor (Version 1.1; Kim, 2015). Data analytic scripts are available at https://osf.io/m9sw3/.

Results

All additional online material is available at https://osf.io/m9sw3/.

After dropping participants from the 4d occupational groups with less than 25 participants and randomly sampling 1,000 participants from groups with over 1,000 participants, the data contained 263 occupational groups. Of those, 37 groups had 25–49 participants, 62 groups 50–99 participants, 91 groups 100–249 participants, 42 groups 250–499 participants, 19 groups 500–999 participants, and 12 groups 1,000 participants (sample sizes for all groups are shown in additional online material Table S2 at https://osf.io/y735x).

The Magnitudes of Occupational Differences in the Big Five Domains

The 4d occupational groups explained between 2% and 7% of the self-reported Big Five domain variance, with openness levels varying the most among jobs (Table 2). Broader occupational groups tended to account for slightly less of the trait variance, suggesting that more specific jobs within broader job groups often differed in average Big Five scores (addressed later).

For comparison, we also calculated the proportions of trait variance explained by occupations without residualizing the domains for age and gender first, as in Wolfram (2023), finding these to be somewhat higher (2%–8%; Table 3). Hence, age and gender differences among incumbents of different jobs accounted for a part of the personality trait differences among them.

Table 2

Variance Proportions (η^2) of the Big Five Domains Accounted for by Jobs Coded Into Four-Digit to Single-Digit ISCO Categories

Big five domain	4d	3d	2d	1d
Neuroticism	.03	.02	.01	.01
Extraversion	.04	.03	.02	.01
Openness	.07	.06	.04	.04
Agreeableness	.02	.01	.01	.01
Conscientiousness	.02	.02	.01	.01

Note. Age and gender controlled for. N = 59,027; 4d = four-digit ISCO codes (k = 263); 3d = three-digit ISCO codes (k = 125); 2d = two-digit ISCO codes (k = 43); 1d = single-digit ISCO codes (k = 10). ISCO = International Standard Classification of Occupations.

Table 3

Variance Proportions (η^2) of the Big Five Domains Accounted for by Jobs Coded Into Four-Digit to Single-Digit ISCO Categories (Age and Gender Not Controlled for)

Big five domain	4d	3d	2d	1d
Neuroticism	.07	.06	.05	.03
Extraversion	.07	.06	.05	.02
Openness	.08	.07	.05	.04
Agreeableness	.04	.03	.02	.01
Conscientiousness	.02	.02	.01	.00

Note. N = 59,027; 4d = four-digit ISCO codes (k = 263); 3d = three-digit ISCO codes (k = 125); 2d = two-digit ISCO codes (k = 43); 1d = single-digit ISCO codes (k = 10). ISCO = International Standard Classification of Occupations.

Mean Big Five Scores of 263 Occupations

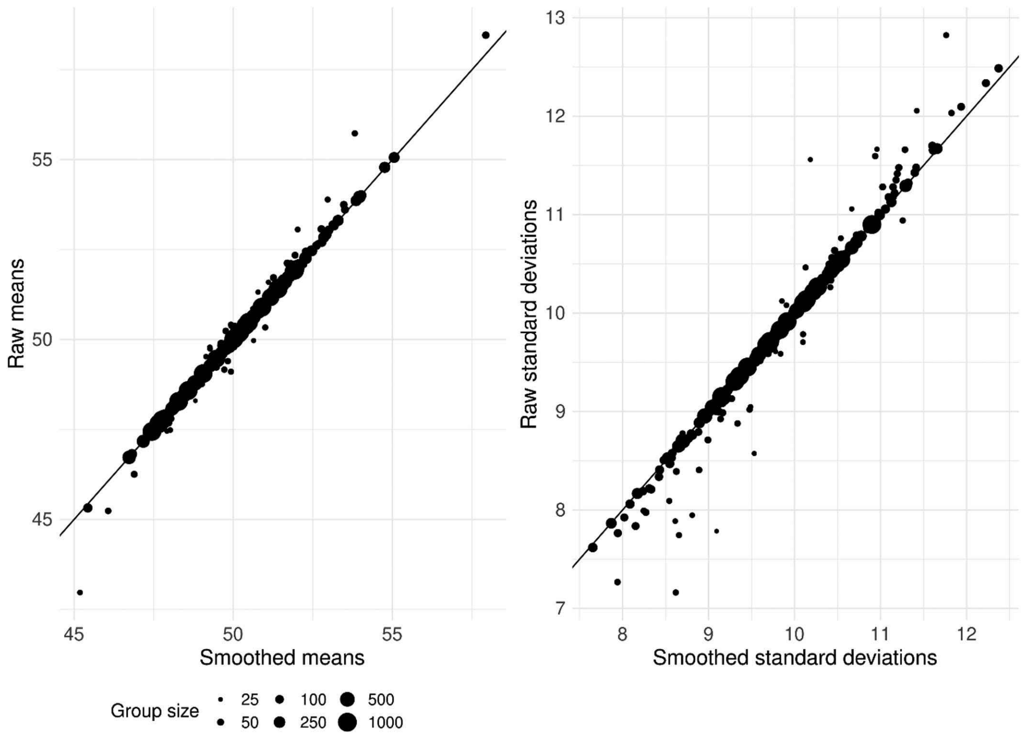
To increase the reliability of the means and *SD*s of the personality trait scores of the 4d job groups, we smoothed them toward the corresponding values of their broader parent job groups inversely proportionally to the group sizes (3d, 2d, or 1d ISCO levels). For the majority of the 4d groups (k = 243), means and *SD*s were smoothed toward their 3d parent group means and *SD*s. With 3d groups fewer than 100 participants, we smoothed the 4d group means/*SD*s toward those of their 2d parent groups (k = 17); where the sample size in 2d groups was also lower than 100, we used 1d groups as the parent group (k = 3; forestry and related workers, garden and horticultural laborers, and kitchen helpers).

The correlations between raw and smoothed group means/*SD*s were very high (Spearman's $\rho > .98$), suggesting that the smoothing did not shift most groups' values much. Figure 2 illustrates these correlations for both means and *SD*s as a function of group size, using the neuroticism domain as an example: As expected, smoothing tended to bring the means and *SD*s of small groups slightly closer to their population-typical values (priors), hence likely increasing their reliability, but it did not affect larger groups. Given this, we used the smoothed means as a basis for establishing the personality profiles of occupations. In additional online material Table S6 at https://osf.io/y735x, we present robustness analyses using alternative weights for the original group means/*SD*s and their parent groups (priors), showing this to have a negligible effect on the results. In addition, we have included nonsmoothed personality scores in additional online material Table S11 at https://osf.io/y735x. For scores not adjusted for sex and age, we provide non-smoothed scores in additional online material Table S12 at https://osf.io/y735x and smoothed scores in additional online material Table S13 at https://osf.io/y735x.

To check whether there were systematic tendencies for smaller occupational groups to have more extreme means and *SD*s (e.g., being outliers), we calculated the correlations of the smoothed 4d group means (specifically, their deviations from 50) and *SD*s with the groups' sizes. The correlations varied from $\rho = -.16$ to .19 (*Mdn* = .02) for means and from $\rho = -.40$ to .28 (*Mdn* = −.15) for *SD*s, suggesting mixed but no systematic relationships between group sizes and the means/*SD*s of their trait scores. This means two things: Less prevalent jobs did not tend to be systematically more extreme or variable in trait scores, and means/*SD*s were not systematically confounded with the group sizes.

Figure 2

Raw and Smooth Means and Standard Deviations of Neuroticism as a Function of Group Size



The 10 highest- and 10 lowest-scoring occupational groups are in Tables 4–8, respectively, for each Big Five domain. For neuroticism, the highest mean scores characterized actors, artists, designers, composers, writers, translators, and journalists, while the lowest mean scores described various managers and leaders, pilots, electronics engineers, and databases/network professionals. For extraversion, the highest average scores pertained to advertising/public relations managers, actors, event planners, fitness instructors, and sports/cultural center managers, whereas electronics engineers, software/multimedia developers, electrical equipment assemblers, and laboratory technicians had the lowest average scores (Table 5). Artists, language teachers, writers, psychologists, university teachers, and research professionals tended to score highest in openness, while plant operators, plumbers, drivers, cabinet-makers, and manufacturing laborers tended to score lowest (Table 6). Average agreeableness scores were the highest among electronics engineers, multimedia developers, psychologists, religious professionals, health professionals, and speech therapists and the lowest among sales workers, entrepreneurs, real estate agents, sales/marketing, as well as administration managers and butchers (Table 7). For conscientiousness, the highest mean scores characterized ships' engineers, dental assistants, construction and finance managers, health professionals, and metalworkers, while the lowest average conscientiousness scores pertained to artists, electronics

Table 4

Jobs With the Highest and Lowest Mean Scores in Neuroticism

Highest-scoring job				Lowest-scoring job			
Job	*M*	*SD*	*N*	Job	*M*	*SD*	*N*
Actors	57.94	10.97	63	Database and network profs. N.E.C.	45.19	10.09	30
Visual artists	55.06	9.60	208	Health services managers	45.44	9.16	127
Graphic and multimedia designers	54.76	10.86	232	Aircraft pilots and rel. associate profs.	46.08	8.25	42
Musicians, singers, and composers	54.03	9.81	188	Finance managers	46.74	10.05	393
Translators, interpreters, and other linguists	53.97	11.29	313	ICT services managers	46.83	10.64	172
Authors and rel. writers	53.96	11.82	41	Electronics engineers	46.90	11.02	50
Journalists	53.87	11.28	219	Managers	46.99	9.43	1,000
Web and multimedia developers	53.82	11.25	38	Unspecified team leaders	47.18	10.33	360
Handicraft workers	53.52	12.22	80	Mining, manufacturing, and construction supervisors	47.37	9.13	304
Broadcasting and audiovisual technicians	53.49	9.42	67	Human resource managers	47.45	9.80	362

Note. *N* = number of people in the sample; profs. = professionals; N.E.C. = not elsewhere classified; rel. = related; ICT = information and communications technology.

Table 5
Jobs With the Highest and Lowest Mean Scores in Extraversion

Highest-scoring job				Lowest-scoring job			
Job	*M*	*SD*	*N*	Job	*M*	*SD*	*N*
Advertising and public relations managers	55.11	9.19	136	Electronics engineers	42.02	12.74	50
Actors	55.01	10.13	63	Software developers	44.90	10.60	876
Conference and event planners	54.83	8.71	29	Web and multimedia developers	44.94	10.07	38
Fitness and recreation instructors and program leaders	54.78	8.39	29	Electrical and electronic equipment assemblers	45.23	9.99	115
Sports, recreation, and cultural center managers	54.55	8.72	84	Software and applications developers and analysts N.E.C.	45.32	11.76	95
Sales and marketing managers	54.29	9.91	1,000	Unspecified laboratory techs./assistants	45.75	9.37	155
Human resource managers	54.17	9.45	362	Database designers and administrators	45.77	10.37	85
Child care services managers	53.98	8.70	97	Pet groomers and animal care workers	45.95	11.34	97
Training and staff development professionals	53.69	9.28	216	Product graders and testers	46.02	10.85	78
Restaurant managers	53.60	10.03	80	(Unspecified) engineering professionals	46.17	10.10	391

Note. *N* = number of people in the sample; N.E.C. = not elsewhere classified; techs. = technicians.

engineers, graphic designers, text editors, journalists, and writers (Table 8). Such distributions of the Big Five domain scores across jobs are generally intuitive and appear to reflect the demands and characteristics of these professions, such as high openness scores among artists and writers and the high conscientiousness among engineers and finance managers. We provide an interactive table at https://apps.psych.ut.ee/JobProfiles/ for all occupations' Big Five profiles, with the input data in additional online material Table S14 at https://osf.io/y735x.

Cross-Validation Using the Traits' Informant Ratings and Data From Wolfram's (2023) Study

We cross-validated the mean self-reported Big Five domain scores against mean informant-reported domain scores. After excluding groups with less than 25 participants (k = 156, N = 1,477) and randomly sampling 1,000 participants from the groups with over 1,000 participants (thereby excluding N = 16 from one group), the sample size with informant ratings was N = 18,496, k = 176. The 4d job groups varied in size: 25–49 (k = 73), 50–99 (k = 55), 100–249 (k = 34), 250–499 (k = 11), 500–999 (k = 3), and over 1,000 participants (k = 1, sampled down to 1,000). Detailed groups and sample sizes are provided in the additional online material Table S3 at https://osf.io/y735x.

According to informant ratings, the 4d occupational groups explained similar proportions of Big Five domain variances as in self-reports, with η^2 = .07 for openness, .04 for extraversion, and .03 for neuroticism, agreeableness, and conscientiousness.

We smoothed the means and *SD*s of the informant-rated personality domains of the 4d job groups similarly to smoothing self-reports; as for self-reported scores, the correlations between raw and smoothed means and variances were very high (Spearman's $\rho >$ .97), suggesting that the smoothing did not change the occupation's rankings much. The correlations between the corresponding mean scores of self- and informant-rated domains of the 4d occupational groups were high, ranging from .63 to .90 (Table 9). This shows that the rankings of the occupations in the Big Five are relatively robust to the method of personality assessment. The correlations between self- and informant-rated variances were lower, although statistically significant (Table 10).

We also analyzed the self-informant correlations between the smoothed domain means and *SD*s among only those participants

Table 6
Jobs With the Highest and Lowest Mean Scores in Openness

Highest-scoring job				Lowest-scoring job			
Job	*M*	*SD*	*N*	Job	*M*	*SD*	*N*
Visual artists	58.52	9.53	208	Crane, hoist, and rel. plant operators	43.95	8.94	48
Language teachers	57.04	10.76	87	Plumbers and pipe fitters	44.72	10.15	50
Authors and rel. writers	56.89	8.72	41	Car, taxi, and van drivers	44.85	9.42	513
Psychologists	56.47	8.98	245	Wood treaters, cabinetmakers, and rel. trades workers	45.13	10.10	67
University and higher education teachers	56.18	9.44	1,000	Manufacturing laborers	45.14	10.01	502
Research professionals N.E.C.	56.07	9.40	70	Bus and tram drivers	45.18	9.71	221
Actors	55.66	8.81	63	Mobile farm and forestry plant operators	45.50	10.40	136
ICT services managers	55.56	10.33	172	Transport and storage laborers	45.56	8.93	64
Religious professionals	55.56	9.64	29	Kitchen helpers	45.93	11.69	72
Secondary education teachers	55.40	9.64	45	Accounting and bookkeeping clerks	45.94	8.94	182

Note. *N* = number of people in the sample; rel. = related; N.E.C. = not elsewhere classified; ICT = information and communications technology.

Table 7
Jobs With the Highest and Lowest Mean Scores in Agreeableness

Highest-scoring job				Lowest-scoring job			
Job	*M*	*SD*	*N*	Job	*M*	*SD*	*N*
Electronics engineers	55.71	9.81	50	Unspecified sales workers	46.72	9.34	36
Web and multimedia developers	54.63	8.91	38	Self-employed/entrepreneurs	47.13	9.94	610
Psychologists	54.34	9.87	245	Real estate agents, property managers	47.28	10.66	199
Religious profs.	54.11	10.44	29	Sales, marketing managers	47.31	10.13	1,000
Health profs. N.E.C.	53.36	11.18	59	Butchers	47.35	9.86	40
Audiologists and speech therapists	53.16	9.49	122	Business services and admin. mgrs. N.E.C.	47.49	10.00	255
Child care services managers	53.06	10.04	97	Chefs	47.61	10.01	115
Software developers	52.96	10.16	876	Unspecified board members	47.69	10.14	626
Research profs. N.E.C.	52.61	9.38	70	Building finishers and rel. workers (unsp.)	47.74	10.12	140
Garment patternmakers/cutters	52.60	9.38	68	Construction managers	47.74	8.59	108

Note. N = number of people in the sample; profs. = professionals; N.E.C. = not elsewhere classified; admin. = administration; mgrs. = managers; rel. = related; unsp. = unspecified.

with both self-ratings and informant ratings ($N = 18{,}490$, $k = 176$). This resulted in a slight increase in the self-informant correlations for means/*SD*s, apart for conscientiousness *SD*s: r = .74/.41 for neuroticism, r = .86/.40 for extraversion, r = .92/.41 for openness, r = .70/.33 for agreeableness, and r = .78/.17 for conscientiousness; $p < .001$ for all correlations apart from conscientiousness *SD*s ($p < .05$). For reference, we also modified the sample to include only those self-reporting participants who did *not* have informant ratings ($N = 45{,}498$, $k = 263$), ensuring that there were no participants who were rated both by an informant and themselves. The correlations of means/*SD*s based on these independent subsamples were as follows: r = .64/.16 for neuroticism, r = .79/.17 for extraversion, r = .86/.12 for openness, r = .47/.12 for agreeableness, and r = .61/.20 for conscientiousness. Correlations of mean scores were significant ($p < .001$), and correlations of *SD* were significant at $p < .05$, except for openness and agreeableness. Such high *cross-method, cross-sample* correlations further demonstrate the robustness of the occupations' Big Five rankings.

As Wolfram (2023) published Big Five mean scores for 360 occupations, of which 217 overlapped with ours, we analyzed the similarity of the occupations' mean scores in the two independent sets of results. Since the domains' means were not residualized for age and sex in Wolfram (2023), for these analyses we did not residualize the Big Five for age and sex either. Despite being based on different countries and very different Big Five questionnaires, occupations' rankings in the Big Five domains were relatively similar in the two data sets, with Spearman's ρs ranging from .48 to .71 (Table 11). Importantly, all convergent correlations exceeded divergent correlations. Had we residualized the scores for age and gender, the correlations had been .25 (agreeableness) to .63 (openness).

Correlations With O*NET Work Styles

The correlations between the smoothed Big Five domain scores and O*NET work styles were analyzed across 213 occupations. Overall, each work style was significantly correlated with at least one Big Five domain (Table 12), although the correlations did not always align with our initial expectations.

Extraversion had significant positive correlations with 14 out of the 16 work styles. The strongest correlations were for self-control ($\rho = .50$, $p < .001$), social orientation ($\rho = .48$, $p < .001$), stress tolerance ($\rho = .47$, $p < .001$), and adaptability/flexibility ($\rho = .46$, $p < .001$). Based on the earlier mapping of work styles onto the Big Five, we expected the highest correlations for leadership and social orientation, which were confirmed, with leadership having a

Table 8
Jobs With the Highest and Lowest Mean Scores in Conscientiousness

Highest-scoring job				Lowest-scoring job			
Job	*M*	*SD*	*N*	Job	*M*	*SD*	*N*
Ships' engineers	53.90	8.50	40	Visual artists	45.55	9.95	208
Dental assistants and therapists	53.68	11.70	25	Electronics engineers	45.92	8.57	50
Construction managers	53.45	9.12	108	Graphic and multim. designers	46.03	10.80	232
Finance managers	53.42	8.99	393	Unsp. editors	46.18	10.98	124
Health profs (unsp.)	53.25	9.47	140	Journalists	46.22	10.59	219
Sheet metal workers	53.07	10.43	34	Authors and rel. writers	46.24	13.34	41
Chefs	52.94	10.03	115	Software developers and analysts N.E.C.	46.45	10.24	95
Ships' deck crews and rel. workers	52.84	9.79	40	Psychologists	46.46	10.49	245
Ships' deck officers and pilots	52.66	7.96	134	Librarians and rel. information profs.	46.78	9.33	328
Unsp. deputy managers	52.66	8.51	161	Mail carriers and sorting clerks	46.85	10.69	135

Note. N = number of people in the sample; multim. = multimedia; unsp. = unspecified; rel. = related; N.E.C. = not elsewhere classified; profs. = professionals.

Table 9
Correlations Between the Mean Self- and Informant-Reported Big Five Domain Scores of Four-Digit Occupational Groups

	Informant report				
Self-report	1	2	3	4	5
1. Neuroticism	.71	−.18	.07	.31	−.55
2. Extraversion	−.30	.84	.12	−.25	.08
3. Openness	−.05	.12	.90	.15	−.37
4. Agreeableness	.41	−.31	.26	.63	−.39
5. Conscientiousness	−.49	.16	−.36	−.42	.72

Note. k = 176 occupational groups, so correlations at least .25 are significant at p < .001. N = 51,701 for self-reports and N = 18,383 for informant reports.

correlation of ρ = .43 (p < .001). The openness domain also showed significant associations with most work styles. The highest correlations were for persistence (ρ = .59, p < .001), initiative (ρ = .59, p < .001), and achievement/effort (ρ = .58, p < .001). There were also correlations aligning with our initial expectations, including significant associations with innovation (ρ = .56, p < .001), analytical thinking (ρ = .51, p < .001), adaptability/flexibility (ρ = .47, p < .001), leadership (ρ = .37, p < .001), and independence (ρ = .19, p < .05). That extraversion and openness tracked the most with work styles is consistent with these domains varying the most between the occupations in the first place.

We expected conscientiousness to show numerous correlations with work styles (e.g., with achievement/effort, persistence, initiative, attention to detail, and independence), but the data did not support these expectations. However, average conscientiousness did correlate with leadership (ρ = .25, p < .001), dependability (ρ = .18, p < .05), and integrity (ρ = .16, p < .05). Likewise, while neuroticism had the expected negative correlations with integrity (ρ = −.28, p < .001) and stress tolerance (ρ = −.17, p < .05), the hypothesized correlations with self-control and adaptability/flexibility did not emerge. Instead, there were unexpected correlations with analytical thinking (ρ = −.35, p < .001), leadership (ρ = −.32, p < .001), persistence (ρ = −.20, p < .01), initiative (ρ = −.19, p < .05), and achievement/effort (ρ = −.16, p < .05). No significant correlations were found between agreeableness and work styles, consistently with this domain varying the least between occupations.

Table 10
Correlations Between the Standard Deviations of Four-Digit Occupational Groups' Self- and Informant-Reported Big Five Domain Scores

	Informant report				
Self-report	1	2	3	4	5
1. Neuroticism	.29	.05	−.01	−.05	−.03
2. Extraversion	.16	.32	.22	−.01	.04
3. Openness	.09	.27	.28	.08	−.03
4. Agreeableness	.01	.02	.09	.25	−.08
5. Conscientiousness	.21	.06	.03	−.13	.23

Note. k = 176 occupational groups, so correlations at least .25 are significant at p < .001. N = 51,701 for self-reports and N = 18,383 for informant reports.

Analyses With Nuances

We compared the 4d occupational groups in 188 items that possibly index partly distinct personality nuances. Similarly to domains, we calculated η^2 for every item, showing the proportion of its variance accounted for by occupational groups. Next, we extracted 23 items with $\eta^2 \geq .04$ and, from these, removed two items with an intercorrelation higher than $r > .50$ with another item to reduce content overlap, keeping the item with higher η^2 from both item pairs. Table 13 presents the remaining 21 items, ordered according to how much of their variance was accounted for by 4d occupational groups. Among these 21 items, seven had been used to compute domain scores (indicated in Table 13). Within these seven items, six loaded onto the openness component and one loaded onto the neuroticism component.

Next, we smoothed the items' mean scores and *SD*s of the 4d occupational groups toward those of their parent groups, similarly to domains-based analyses. The correlations between the raw and the smoothed means/*SD*s were high, exceeding ρ > .99/.97 for all items. For each item, the smoothed means and *SD*s for three top- and bottom-scoring occupations are given in Table 14. For example, intuitively, the mean scores "Want to be in charge" were the highest among different managers, team leaders, or senior government officials, while the lowest mean scores characterized roles that typically do not involve high-level decision making or leadership obligations, such as clerks, helpers, and market salespersons. Expectedly, artists, actors, and musicians tended to score the highest on "Need a creative outlet," and writers, journalists, and translators tended to score the highest on "Have a rich vocabulary." We provide an interactive table at https://apps.psych.ut.ee/JobProfiles/, showing all occupations' item-score rankings.

Similar to domains, we cross-validated self-reported means and *SD*s against corresponding values in informant reports, smoothed similarly to self-reports. Again, informant-reported items' smoothed means/*SD*s were strongly correlated with raw means/*SD*s, with ρ > .97/.91. Correlations between self- and informant-rated smoothed means for items were high, ranging from ρ = .67 to .92 (*Mdn* = .85; Table 15), although the correlations of *SD*s were lower and in some cases statistically insignificant, ρ = −.08 to .70 (*Mdn* = .24). So, items' mean scores replicated strikingly well across methods, whereas items' variances were more method-specific/unreliable.

MDS

Figures 3 and 4 present the maps of occupational trait profiles based on the five domains and 21 nuances, respectively. We used classical MDS to reduce the 5/21 dimensional means into two dimensions, rotating these toward extraversion and openness in the case of domains-based and toward neuroticism and openness in the case of nuance-based dimensions, since these were the domains the dimensions were most correlated with.

The 4d occupational groups belonging to the same broadest hierarchical groups (1d, indicated with distinct colors) also tended to cluster closer based on their personality profiles. There were several exceptions, however. For example, based on both domains and nuances, travel guides were closer to (language) teachers and public relations professionals than to other service workers, possibly indicating shared psychological characteristics among these groups. Likewise, several technician and associate professional jobs according to the ISCO-08 1d level were further away from other

Table 11
Correlations of the Four-Digit Occupational Group Means With Those in Wolfram (2023)

	Wolfram's study				
This study	1	2	3	4	5
1. Neuroticism	.40	.09	.01	.21	−.37
2. Extraversion	.15	.56	.25	.23	.28
3. Openness	.14	−.11	.63	−.05	.01
4. Agreeableness	.17	−.14	.08	.25	−.12
5. Conscientiousness	−.26	.00	−.34	−.12	.42

Note. $k = 217$ occupational groups. All correlations over .22 are significant at $p < .001$.

jobs in that group. For example, photographers, broadcasting-audiovisual technicians, and artistic–cultural associate professionals were personality profiles-wise more similar to artistic professions, suggesting they may have creative characteristics and tasks that distinguish them from other technically oriented jobs. The locations of more creative–artistic occupations (e.g., visual artists, authors, actors) stand out in Figure 4, as these jobs are on the highest end of the vertical/openness dimension. Conversely, the lowest end of this dimension is occupied by occupations tending more toward elementary roles (including machine operators). For another example, while managers, regardless of their specific area of expertise—be it finance, child care services, or cultural activities—tended to cluster along the horizontal axis, they varied substantially along the other axis. In the domains-based MDS (Figure 3), for example, they all leaned toward the higher end of the extraversion-dominated axis, whereas advertising/public relations managers and information technology managers had high but sales managers and supply/distribution managers lower mean scores in the openness-dominated axis.

Table 12
*Correlations Between Big Five Domains and O*NET Work Styles Evaluations*

O*NET work style	E	O	N	C	A
Achievement/effort	.32	.58	−.16	.06	−.02
Persistence	.33	.59	−.20	.08	.06
Initiative	.44	.59	−.19	.09	−.01
Leadership	.43	.37	−.32	.25	−.12
Cooperation	.39	.30	−.04	.02	.10
Concern for others	.41	.08	−.05	.12	.08
Social orientation	.48	.13	−.06	.09	.03
Self-control	.50	.09	−.12	.15	−.01
Stress tolerance	.47	.25	−.17	.18	−.12
Adaptability/flexibility	.46	.47	−.12	−.01	.10
Dependability	.45	.26	−.09	.18	<.01
Attention to detail	−.10	.21	−.02	.08	−.10
Integrity	.36	.31	−.28	.16	.05
Independence	.23	.19	.01	.04	.10
Innovation	.17	.56	−.02	−.06	.15
Analytical thinking	−.04	.51	−.35	.11	.07

Note. $k = 213$ occupational groups. All p values are adjusted for false discovery rate; correlations over .25 are significant at $p < .001$, over .20 at $p < .01$, and over .16 at $p < .05$. O*NET = Occupational Information Network database; E = extraversion; O = openness; N = neuroticism; C = conscientiousness; A = agreeableness.

We provide an interactive version of the domains-base plot in https://apps.psych.ut.ee/JobProfiles/.

Homogeneity Analyses

We calculated the correlations between the mean scores and *SD*s of the Big Five domains of the 4d occupational groups to investigate whether higher mean levels were associated with increased variance for neuroticism and reduced variance for the other domains. The associations between the smoothed means and *SD*s were statistically significant ($p < .01$) for four traits: $\rho = .29$ for neuroticism, $\rho = -.32$ for extraversion, $\rho = -.16$ for openness, and $\rho = -.42$ for conscientiousness (Figure 5). In the additional online material Table SM1 at https://osf.io/y735x, we also present the correlations with raw means and *SD*s, which were similar in magnitude. To ensure the robustness of these results, we also found similar associations between means and *SD*s, controlling for sample size in a series of multiple regressions (see additional online material at https://osf.io/m9sw3/).

The associations between informant-rated means and *SD*s ($k = 176$) were statistically significant ($p < .001$) for extraversion ($\rho = -.31$) and conscientiousness ($\rho = -.31$). For agreeableness, the correlation between the means and *SD*s of the informant-rated domain was stronger ($\rho = -.24$, $p < .01$) than the correlation for self-reported agreeableness. However, the correlations for neuroticism ($\rho = .14$) and openness ($\rho = -.15$) were not statistically significant in informant ratings ($p > .05$). Finally, since combining self-ratings and informant ratings may yield more reliable means and *SD*s than either method alone, we averaged the smoothed means and *SD*s based on self-ratings and informant ratings for the 176 occupations with available data. In these data, means and *SD*s were significantly correlated for all domains: $\rho = .23$, $-.20$, and $-.24$ ($p < .01$) for neuroticism, openness, and agreeableness, and $\rho = -.42$ ($p < .001$) for extraversion and conscientiousness.

Overall, thus, the majority of the findings supported the hypothesis that jobs with higher average levels of traits that are typically associated with better job performance tend to be more homogenous in these traits than jobs with lower average performance-related trait levels. This was especially notable for extraversion and conscientiousness.

We further examined the impact of performance indicators, such as income and SIOPS prestige scores, on these relationships. Including income or SIOPS scores in the analyses attenuated the mean–*SD* correlation for self-reported openness to nonsignificance, suggesting that this association may be largely attributable to differences in income levels and job prestige. In informant reports, the same happened only when controlling for SIOPS scores. For other personality traits, the correlations remained largely unchanged after controlling for income or SIOPS scores. We provide details of these analyses in the additional online material Tables SM4–SM5 at https://osf.io/y735x. In summary, the mean–*SD* correlations were relatively robust to controlling for other job characteristics, except for openness.

Discussion

This study is the most extensive published effort to date to map occupational personality profiles. We used a sample of nearly 69,000 participants who represented 263 ISCO-coded occupations, comprehensively assessed personality domains and nuances with

Table 13
Variance Proportions (η^2) of the Items Accounted for by Jobs Coded Into Four-Digit to Single-Digit ISCO Categories

Item	4d	3d	2d	1d
1. Want to be in charge	.12	.11	.10	.09
2. Try to avoid speaking in public	.09	.08	.06	.05
3. Need a creative outlet	.09	.07	.04	.01
4. Am interested in science[a]	.08	.07	.05	.04
5. Like to solve complex problems[a]	.07	.06	.05	.04
6. Have a natural talent for influencing people	.06	.06	.04	.04
7. Have a rich vocabulary[a]	.06	.06	.04	.03
8. Believe in the importance of art[a]	.06	.05	.03	.02
9. Support liberal political candidates	.06	.05	.04	.04
10. Like to stand out in a crowd	.06	.05	.04	.03
11. See myself as an average person	.05	.04	.03	.02
12. Avoid philosophical discussions[a]	.05	.04	.03	.03
13. Try to outdo others	.05	.04	.03	.03
14. Am considered to be a wise person[a]	.05	.04	.03	.03
15. Become anxious in new situations	.04	.04	.03	.03
16. Believe that we should be tough on crime	.04	.04	.03	.02
17. Like to read	.04	.04	.03	.02
18. Believe in the power of fate	.04	.03	.02	.02
19. Tend to feel very hopeless	.04	.03	.03	.02
20. Adapt easily to new situations	.04	.03	.02	.02
21. Cannot make up my mind[b]	.04	.03	.02	.02

Note. N = 59,027. 4d = four-digit ISCO codes (k = 263); 3d = three-digit ISCO codes (k = 125); 2d = two-digit ISCO codes (k = 43); 1d = single-digit ISCO codes (k = 10). ISCO = International Standard Classification of Occupations; PCA = principal component analysis.
[a] These items were loaded onto the openness component in the PCA.
[b] Item loaded onto the neuroticism component in the PCA.

self-reports, and cross-validated the results with informant ratings for nearly 20,000 individuals. Controlling for age and gender, occupations accounted from 2% to 7% of the Big Five domain variance and up to 12% of the variance in single-item nuances. Occupations' rankings in the domains and nuances were generally intuitive, aligned with our expectations based on previous but less comprehensive studies and indirect evidence, and replicated well across assessment methods. Further strengthening the findings' validity, the domains' rankings were similar to those found in a different sociocultural context but with a minimalist personality questionnaire (Wolfram, 2023). Often, occupations' average trait scores also tracked with O*NET work style ratings, although some intuitive associations were missing, and they generally clustered along the ISCO's hierarchical structure. Finally, occupations with higher average levels of the traits usually related to better job performance tended to be more homogeneous in these traits. This suggests that jobs do not differ only in typical trait levels but also in how strongly their incumbents (have to) match these levels. We provide an interactive application for exploring these findings (https://apps.psych.ut.ee/JobProfiles/).

The Magnitudes of Occupational Differences

We anticipated that occupations would account for somewhat more variance in personality domains than 2%–7%, given that we assessed domains more comprehensively than previous comparable studies and covered a broad range of occupations classified into the narrowest occupational groups. For instance, Törnroos et al. (2019) reported that more broadly classified occupations accounted for 1%–4% of the variance in the Big Five personality traits, while they only assessed the domains with three items each; in our data, broader occupational groups also explained less variance. With equally minimalist Big Five assessments, occupations classified with a comparable granularity to our study explained 7%–10% of the Big Five variance in Wolfram (2023).

What could explain this? First, similarly to us, Törnroos et al. (2019) controlled for age and gender, but Wolfram (2023) did not; had we not done this, occupations had also explained slightly more of the Big Five variance in our data but still not as much as in Wolfram. Second, sociocultural circumstances and the classification of occupations may have each played a role. For example, occupations may be less stratified by personality traits in Estonia than in the United Kingdom, although both of the other studies were based on the United Kingdom and yet yielded different results. Additionally, the differences between Wolfram's Standard Occupational Classification and our ISCO classification system could have influenced the variance explained in the Big Five traits. Third, Wolfram's use of external-to-trait-ratings information (from the O*NET database) in the calculations may have contributed to larger occupational differences. Fourth, high intercorrelations (up to r = ∼.50; Lang et al., 2011) among some domain scores in the short 15-item Big Five Inventory (BFI-S) used by Wolfram likely inflated the estimates for individual domains, with the same variance varying between occupations under different domain labels.

Fifth, it is possible that subtraits of the broad Big Five domains vary more across occupations than the domains themselves, as is common for many life outcomes (e.g., Seeboth & Mõttus, 2018; Speer et al., 2022; Stewart et al., 2022). Incidentally, these subtraits may have been covered in the narrowly defined domain assessments in Wolfram at the expense of other subtraits that happen to vary less with occupations, inflating the domains' variability across domains. This possibility is consistent with our findings that many single-item personality nuances varied more along occupations than the broad domains. For example, we found that items "Want to be in charge," "Try to avoid speaking in public," "Am interested in science," and "Need a creative outlet" showed more variance across different occupations compared to the broader domains these items could be associated with, despite single items being less reliable than multi-item domain scores. For example, the item "Try to avoid public speaking" maps onto the neuroticism domain, particularly its anxiety component. The anxiety component was also prominently represented in the neuroticism scale of the BFI-S used by Wolfram, being measured by all of its three items: "Worries a lot," "Gets nervous easily," and, inversely, "Remains calm in tense situations." So, the BFI-S may incidentally capture the most job-related component of neuroticism, omitting other neuroticism facets such as depressiveness, hostility, self-consciousness, and impulsiveness. Likewise, the other Big Five domains were not comprehensively assessed by the BFI-S due to having only three items per domain, while our assessment incorporated a broader range of subtraits, allowing the domains to be defined more thoroughly. In conclusion, narrowly defined and minimalist personality assessments may partly misrepresent occupational personality trait differences. Moreover, personality facets and nuances may help to differentiate between

Table 14
Occupations With the Highest and Lowest Mean Scores in Personality Nuances

High				Low			
Job	*M*	*SD*	*N*	Job	*M*	*SD*	*N*
Want to be in charge							
Child care services mgrs.	58.79	8.48	97	Filing and copying clerks	44.18	8.97	58
Education mgrs.	58.5	8.03	434	Kitchen helpers	44.21	9.66	72
Mgrs.	58.07	8.18	1,000	Teachers' aides	44.81	9.27	450
Try to avoid speaking in public							
Medical and dental prosthetic techs.	55.72	8.62	61	Education mgrs.	42.2	8.72	434
Shoemakers and rel. workers	55.33	8.31	27	Religious profs.	42.2	9.53	29
Electrical and electronic equipment assemblers	54.7	8.35	115	Advertising and public relations mgrs.	42.22	9.15	136
Need a creative outlet							
Visual artists	63.44	5.85	208	Accounting and bookkeeping clerks	45.31	9.53	182
Actors	62.74	6.31	63	Accounting associate profs.	45.44	9.37	1,000
Musicians, singers, and composers	62.22	6.42	188	Livestock and dairy producers	45.58	10.05	121
Am interested in science							
Research profs. N.E.C.	60.46	6.69	70	Kitchen helpers	44.07	12.8	72
University and higher education teachers	60.02	6.89	1,000	Earthmoving and rel. plant operators	44.48	10.27	101
Biologists, botanists, zoologists, and rel. profs.	57.56	9.17	57	Crane, hoist, and rel. plant operators	44.9	11.4	48
Like to solve complex problems							
ICT services mgrs.	56.47	8.49	172	Mobile farm and forestry plant operators	44.63	9.66	136
Research and development mgrs.	55.13	8.99	315	Forestry and rel. workers	45.11	8.94	65
Database and network profs. N.E.C.	55.05	8.27	30	Handicraft workers	45.16	11.12	80
Have a natural talent for influencing people							
Human resource mgrs.	55.82	8.85	362	Printers	44.91	11.39	48
Psychologists	55.43	8.85	245	Web and multimedia developers	44.91	10.81	38
Social welfare mgrs.	55.25	8.75	44	Electronics engineers	45.04	10.84	50
Have a rich vocabulary							
Authors and related writers	58.43	8.84	41	Printers	44.4	10.59	48
Journalists	57.98	8.76	219	Electrical and electronic equipment assemblers	44.5	10.42	115
Translators, interpreters, and other linguists	57.57	8.9	313	Prepress techs.	44.64	10.51	37
Believe in the importance of art							
Actors	61.96	6	63	Earthmoving and rel. plant operators	43.95	10.8	101
Visual artists	61.27	4.5	208	Mobile farm and forestry plant operators	44.15	11.02	136
Musicians, singers, and composers	61.26	6.13	188	Heavy truck and lorry drivers	45.01	10.14	126
Support liberal political candidates							
Authors and rel. writers	57.52	9.56	41	Religious profs.	43.06	14.63	29
Film and rel. directors and producers	55.13	10.51	118	Heavy truck and lorry drivers	43.78	12.15	126
ICT services mgrs.	54.88	8.73	172	Crane, hoist, and rel. plant operators	44.46	10.8	48
Like to stand out in a crowd							
Actors	56.49	9.35	63	Garden and horticultural laborers	45.32	9.4	26
Advertising and public relations mgrs.	55.96	8.4	136	Manufacturing laborers	45.4	10.1	502
Film and rel. directors and producers	54.9	8.3	118	Welders and flame cutters	45.55	9.45	80
See myself as an average person							
Wood treaters, cabinetmakers, and rel. trades workers	54.99	7.96	67	Visual artists	40.02	11.78	208
Transport and storage laborers	54.77	8.05	64	Authors and rel. writers	40.68	13.48	41
Livestock and dairy producers	54.3	8.04	121	Actors	42.05	12.37	63
Avoid philosophical discussions							
Crane, hoist, and rel. plant operators	56.31	9.7	48	Visual artists	43.14	9.02	208
Mobile farm and forestry plant operators	54.79	10.26	136	Psychologists	43.49	8.79	245
Manufacturing laborers	54.46	10.06	502	Film and rel. directors and producers	43.82	8.32	118
Try to outdo others							
Research and development mgrs.	55.14	8.59	315	Filing and copying clerks	45.01	9.78	58
Mgrs.	54.34	9.82	1,000	Kitchen helpers	45.03	10.12	72
Finance mgrs.	54.27	9.17	393	Teachers' aides	45.4	9.46	450
Am considered to be a wise person							
Training and staff development profs.	55.24	8.95	216	Kitchen helpers	43.71	12.54	72
Language teachers	54.77	9.62	87	Sewing, embroidery, and rel. workers	44.98	11.78	291
Psychologists	54.74	9.13	245	Elementary workers N.E.C.	45.21	11.02	185
Become anxious in new situations							
Web and multimedia developers	54.68	9.79	38	Aircraft pilots and rel. associate profs.	44.56	9.52	42
Medical and dental prosthetic techs.	54.44	9.8	61	Senior government officials	45.17	10.23	207
Pet groomers and animal care workers	54.3	10.31	97	Advertising and public relations mgrs.	45.34	10.04	136
Believe that we should be tough on crime							
Statistical, mathematical, and rel. associate profs.	54.33	8.42	50	Religious profs.	39.98	12.33	29
Toolmakers and rel. workers	53.72	8.46	87	Psychologists	40.84	10.01	245

(*table continues*)

Table 14 (*continued*)

High				Low			
Job	*M*	*SD*	*N*	Job	*M*	*SD*	*N*
Dental assistants and therapists	53.71	9.57	25	Judges	41.83	9.57	75
Like to read							
Authors and rel. writers	57.44	7.08	41	Plumbers and pipe fitters	43.64	10.16	50
Journalists	55.63	7.28	219	Spray painters and varnishers	44.34	9.83	36
Research profs. N.E.C.	55.51	8.77	70	Earthmoving and rel. plant operators	44.77	10.84	101
Believe in the power of fate							
Sheet metal workers	54.47	10.29	34	Software developers	43.11	10.36	876
Ships' deck crews and rel. workers	53.91	10.4	40	Religious profs.	43.18	11.92	29
Chefs	53.58	9.93	115	Research profs. N.E.C.	43.4	9.54	70
Tend to feel very hopeless							
Mail carriers and sorting clerks	55.79	10.81	135	Aircraft pilots and rel. associate profs.	44.53	6.89	42
Pet groomers and animal care workers	54.9	12.04	97	Psychologists	44.92	8.34	245
Waiters	54.53	11.79	216	Database and network profs. N.E.C.	45.87	9.04	30
Adapt easily to new situations							
Aircraft pilots and rel. associate profs.	54.71	7.38	42	Filing and copying clerks	45.45	9.81	58
Air traffic controllers	54.44	7.96	26	Kitchen helpers	45.71	12.12	72
Human resource mgrs.	54.39	8.06	362	Elementary workers N.E.C.	45.87	10.9	185
Cannot make up my mind							
Toolmakers and rel. workers	53.91	9.13	87	Judges	44.66	8.92	75
Web and multimedia developers	53.75	9.91	38	Senior government officials	45.84	9.47	207
Actors	53.73	10.46	63	Aircraft pilots and rel. associate profs.	45.85	9.17	42

Note. N = number of people in the group; mgrs. = managers; techs. = technicians; rel. = related; profs. = professionals; N.E.C. = not elsewhere classified; ICT = information and communications technology.

occupations better than domains, especially when the descriptive simplicity and cross-study comparability provided by the Big Five are less critical.

How Different Were the Highest- and Lowest-Scoring Occupations?

The η^2s provided us with one way to show how much occupations varied in personality traits, with their values broadly in line with typical effect sizes in psychology and other kinds of group differences in personality traits (e.g., age, gender, ethnic background). However, as we compared traits across 263 occupational groups, these groups' average trait scores would naturally tend toward a normal distribution, just as individuals' scores do, meaning that most jobs' typical trait scores differed relatively little, but there would be tails with more extreme values.

Therefore, one alternative way to grasp the extent of occupational differences in average personality scores is to compare these tails.

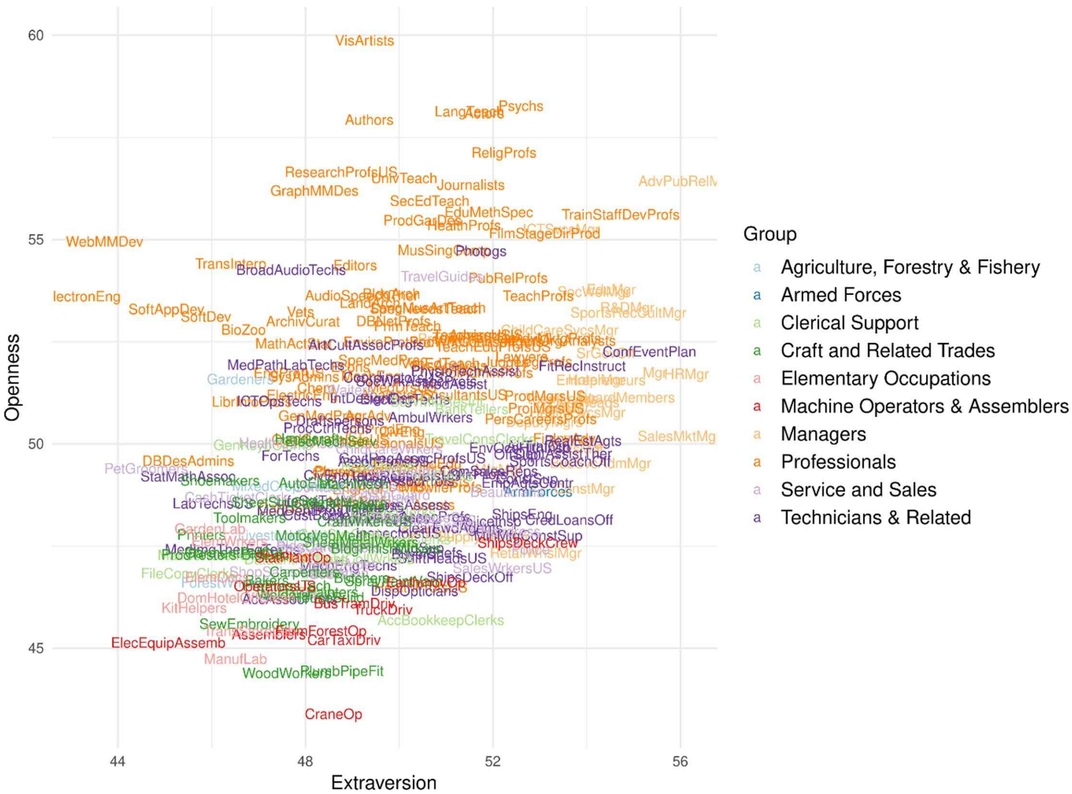
Table 15
Correlations Between Mean Self- and Informant-Reported Item Scores

Item	Correlation between mean score (ρ)	Correlation between variance (ρ)
Want to be in charge	.67	.26
Try to avoid speaking in public	.70	.18
Need a creative outlet	.72	.43
Am interested in science	.74	.55
Like to solve complex problems	.74	.14
Have a natural talent for influencing people	.78	.21
Have a rich vocabulary	.81	.40
Believe in the importance of art	.82	.47
Support liberal political candidates	.84	.54
Like to stand out in a crowd	.84	.08
See myself as an average person	.85	.37
Avoid philosophical discussions	.85	.08
Try to outdo others	.86	.12
Am considered to be a wise person	.87	.33
Become anxious in new situations	.87	.03
Believe that we should be tough on crime	.88	.19
Like to read	.89	.70
Believe in the power of fate	.90	.17
Tend to feel very hopeless	.90	.24
Adapt easily to new situations	.90	.25
Cannot make up my mind	.92	−.08

Note. k = 176 occupational groups, so correlations at least .25 are significant at $p < .001$. N = 51,701 for self-reports and N = 18,383 for informant reports.

Figure 3

Multidimensional Scaling of Occupational Groups' Trait Profiles Based on Domains



Note. $N = 59{,}027$, $k = 263$. Shortened job titles are defined in additional online material Table S2 at https://osf.io/y735x. An interactive version of the figure with full job titles and Big Five domain scores is available at https://apps.psych.ut.ee/JobProfiles/. See the online article for the color version of this figure.

For example, if we average the average trait scores of the bottom and top 10 occupational groups for each Big Five domain (Tables 4–8; graphically represented in Figure 6), the top and bottom 10 occupations differ by between 6.25 (agreeableness) and 11.14 (openness) *T*-score points (i.e., 0.625–1.14 *SD*s, respectively); for neuroticism, extraversion, and conscientiousness, these values were 7.81, 9.19, and 6.91 *T*-score points. None of these differences is small by psychology's conventional standards (e.g., Funder & Ozer, 2019). Given that there were 74 unique groups among the 100 occupational groups with bottom or top scores in the Big Five domains, many occupational groups (74/263 means 28%) can be characterized by at least one fairly distinctive average Big Five domain score. More specifically, 114 occupations (43%) had at least one average Big Five score at least |0.3| *SD*s from the population mean of 50, whereas 11 (4%) had at least one average score at least |0.50| *SD* from the population mean. So, not all jobs have distinctive personality profiles, but many do.

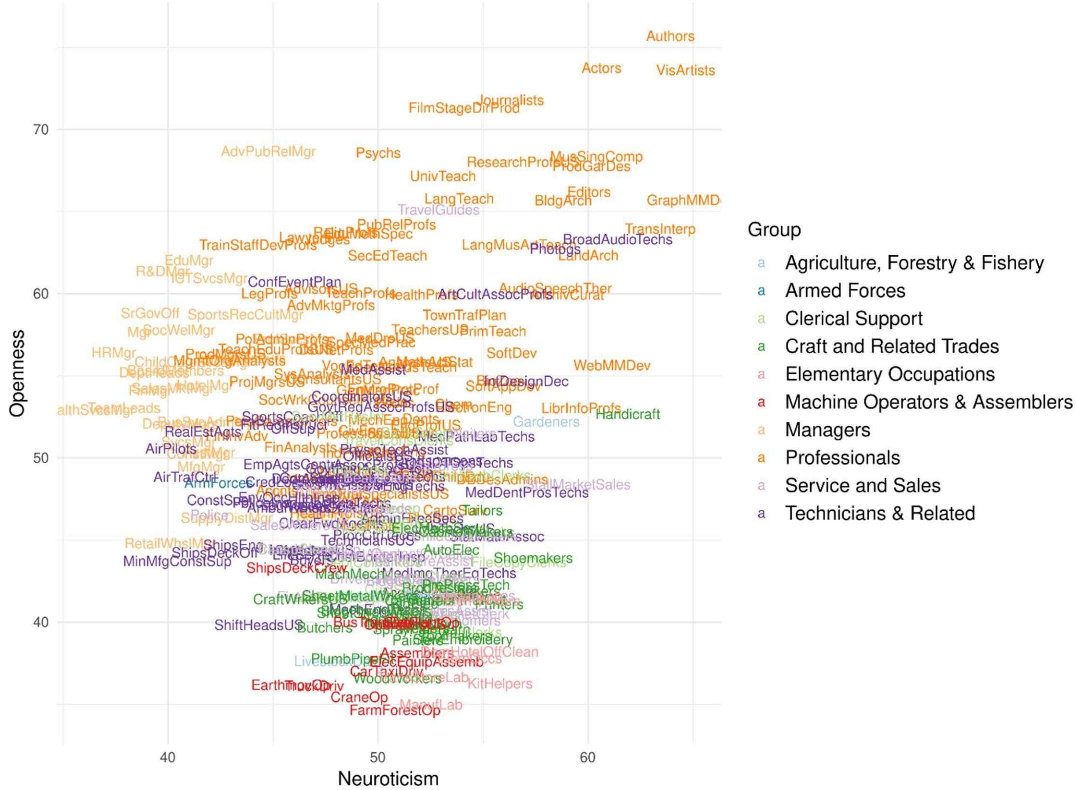
How Do Specific Occupations Compare in Personality Traits?

We calculated average trait scores for 263 occupations coded into the 4d (unit) ISCO job categories. For more reliable estimates, we smoothed these averages toward those of the broader (parent) occupational groups (generally, 3d), inversely proportionally to the 4d groups' sizes. For example, with the smallest possible 4d group sizes, 25, the smoothed average was halfway between the original 4d group's average and its parent (e.g., 3d) group's average, while with group sizes of 50 and 100, the original 4d group had weights of 80% and 94% (Figure 1). Although such smoothing generally did not change the occupations' trait rankings, it aligned the smaller groups-based estimates (possible outliers) with more trait typical values, hence resulting in more conservative and likely reliable estimates (Figure 2).

Jobs' rankings in the Big Five domains were usually intuitive. For example, jobs with the highest average openness included creative roles, such as artists and writers, and professions generally more open to novel knowledge, like (university) teachers and research professionals. Similarly, roles within the creative sector—such as actors, artists, designers, and writers—also tended to score high in neuroticism and low in conscientiousness. These findings aligned with our expectations (Table 1) based on prior research (Törnroos et al., 2019; Wolfram, 2023), and with a meta-analysis by Vedel (2016) showing that arts and humanities majors often exhibit higher neuroticism and openness scores and lower conscientiousness scores compared to other fields.

Occupations characterized by the lowest average neuroticism mainly included various managers and pilots. These findings also

Figure 4
Multidimensional Scaling of Occupational Groups' Trait Profiles Based on Nuances



Note. N = 59,027, k = 263. Shortened job titles are defined in the additional online material Table S2 at https://osf.io/y735x. See the online article for the color version of this figure.

align with trends observed in previous research focusing on specific groups, such as managers (Lounsbury et al., 2016) and aviation professionals (R. King et al., 2011). In fact, the Estonian Flight Academy uses personality testing in the applicant selection process, prescreening them for stress tolerance (https://lennuakademia.ee/[2]), so pilots' comparatively low average neuroticism has a tractable mechanism. While health professionals, skilled construction positions, and mechanics did not score as high as hypothesized, on average, occupations closely related to these categories appeared in the upper half of the rankings.

The highest conscientiousness scores were found in ship engineers, dental assistants, construction managers, and financial managers, reflecting their core responsibilities that require diligence and attention to detail. For extraversion, jobs typically considered demanding social and outgoing roles, like advertising and public relations managers, actors, and event planners, tended to score the highest. Conversely, occupations involving less social interaction, such as electronics engineers, software/multimedia developers, assemblers, and laboratory technicians, had the lowest average extraversion scores. All these rankings align with our expectations outlined in Table 1.

In the agreeableness domain, it was anticipated that personal care/service, research, and religious professionals would have the highest scores. And indeed, psychologists, religious professionals, and health professionals ranked among the jobs with the highest scores. These findings are consistent with research on personality profiles related to university majors (Vedel, 2016) and previous studies on priests, for example (Cerasa et al., 2016). Surprisingly, electronics engineers and multimedia developers displayed the highest average agreeableness scores, which may not align with typical perceptions of these roles. This was also not in line with our expectations based on earlier studies, as Wolfram (2023) found that electrical engineers were among the occupations with the lowest average agreeableness score. We observed the lowest agreeableness scores among sales workers, entrepreneurs, real estate agents, business services, and sales managers. This tendency may be linked to the job demands in sales and managerial roles, where efficiency, adaptability, and insistence could be more crucial than pleasing people. Our results aligned most closely with the expectations regarding managers, while other jobs anticipated to have the lowest agreeableness scores were also represented among the bottom 20 occupations.

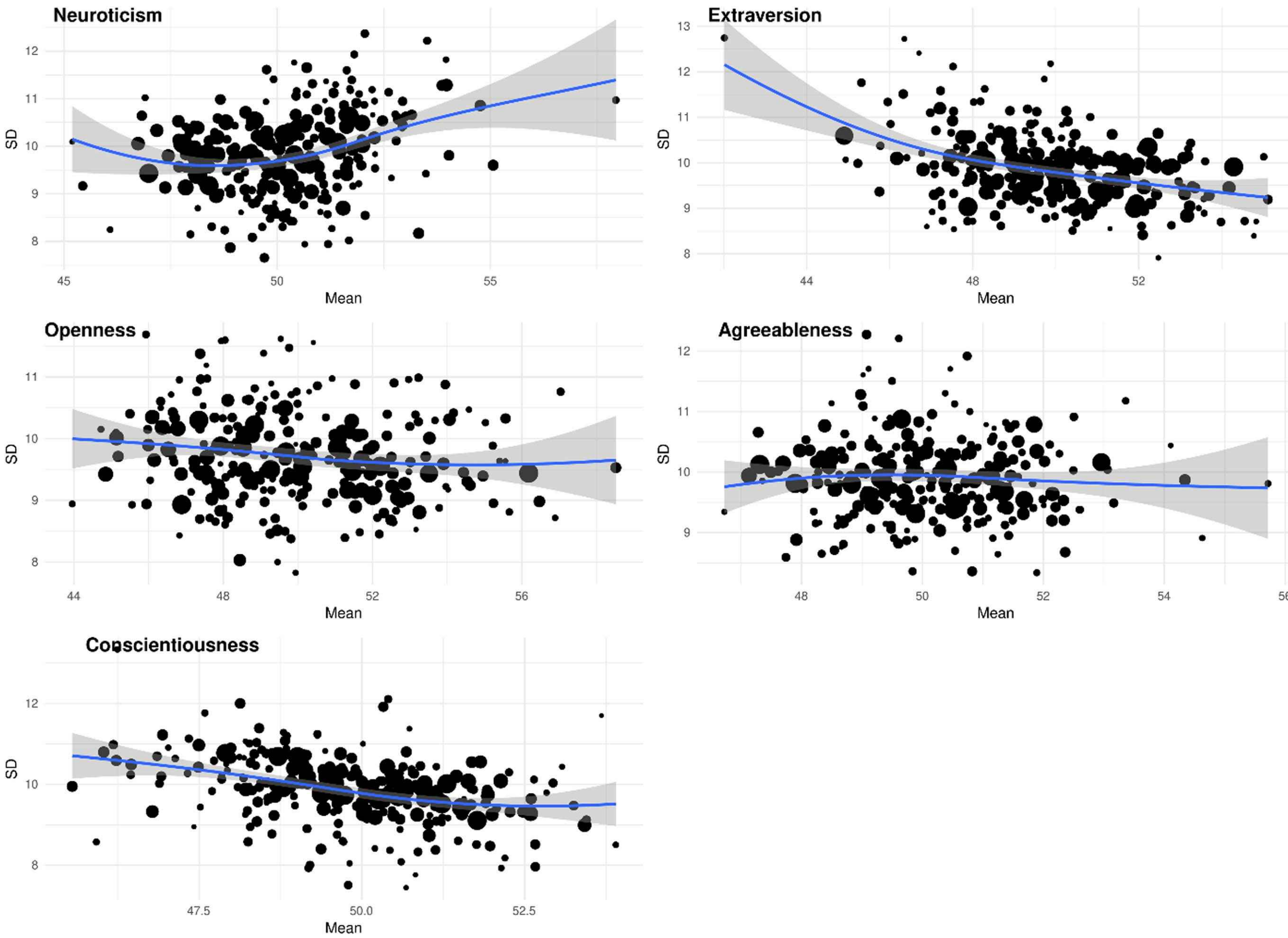
Nuanced Occupational Differences

A unique contribution of our study is the profiling of personality nuances across the 263 occupations, focusing on those that varied the most with jobs, with effect sizes at least equal to typical effect

[2] Waybackmachine archived version: https://web.archive.org/web/20231015195554/https://lennuakadeemia.ee/sisseastumine/sisseastumistingimused/kutsesobivustest-pilootidele.

Figure 5

Correlation Between Mean Scores and Standard Deviations of Big Five Traits in Four-Digit Occupational Groups



Note. See the online article for the color version of this figure.

sizes in psychology ($r \geq .20$, $\eta^2 \geq .04$). This means that most of these nuances varied among the occupations more than most domains. Similarly to domains, the resulting profile patterns were usually highly intuitive (https://apps.psych.ut.ee/JobProfiles/). For example, the nuance represented by the item "Want to be in charge" varied the most with jobs, with the highest scores among various leadership roles and the lowest scores in support roles such as clerks, kitchen helpers, and teachers' aides.

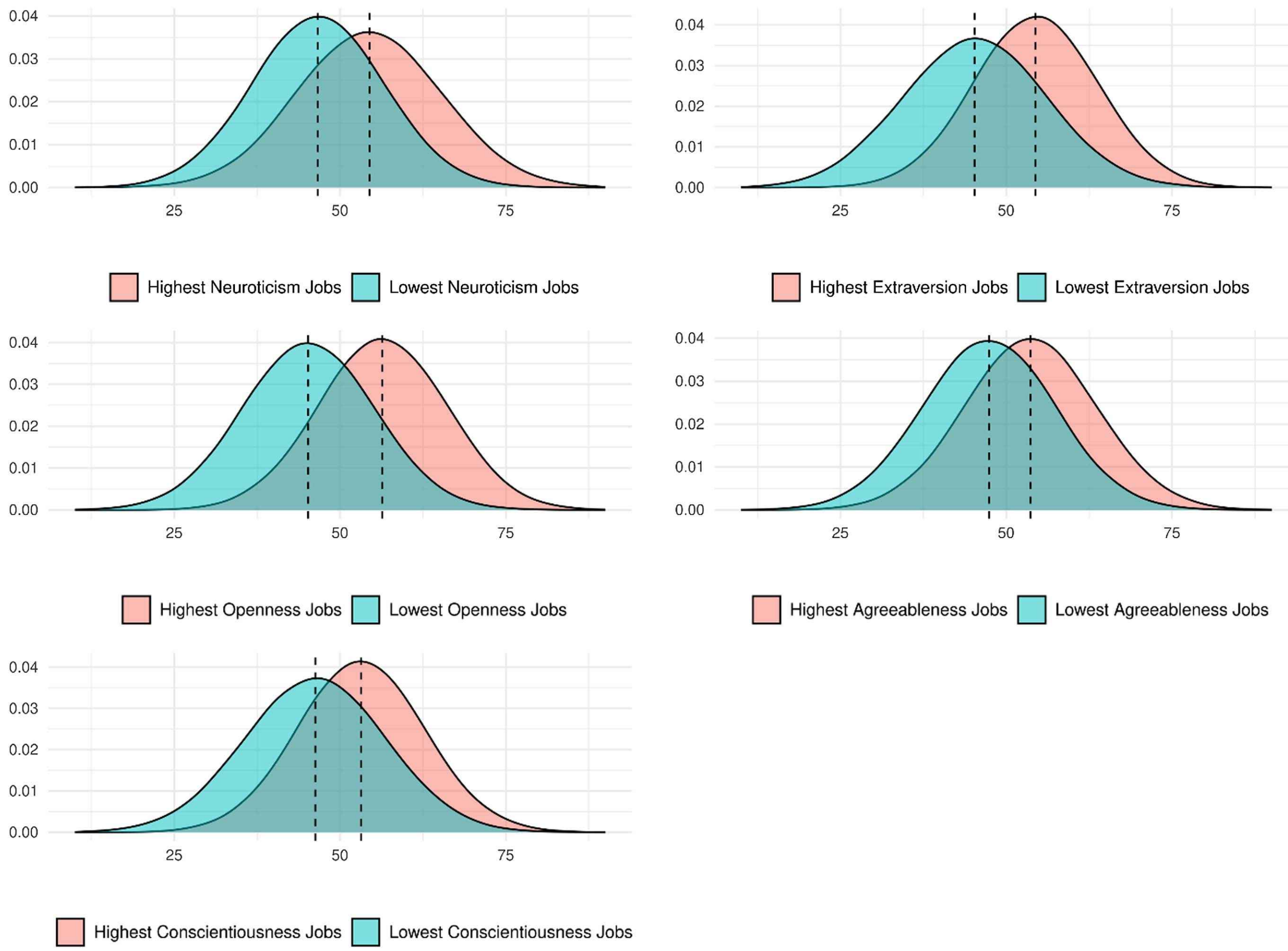
Occupational groups explained substantial proportions of variance in several nuances associated with the openness domain; yet these nuances were not redundant, correlating less than .50, which is far lower than their reliability (Henry & Mõttus, 2023). Consistent with the domain's rankings, various creative professions had the highest mean scores on these nuances. For instance, nuances represented by items like "Need a creative outlet" and "Believe in the importance of art" had the highest mean scores among actors, visual artists, musicians, film directors, and designers. Additionally, occupations like writers, journalists and translators were characterized by high scores on nuance-items such as "Have a rich vocabulary" and "Like to read."

Many other item trends also appeared consistent with the jobs' expected responsibilities and day-to-day activities. For instance, on average, managers did not mind public speaking, liked to solve complex problems, and tried to outdo others. Judges, pilots, and senior government officials tended to find it easiest to make decisions. Equally reassuringly, typical pilots and air traffic controllers found it easy to adapt to new situations, and research-related professionals tended to be interested in science. Likewise, human resources and social welfare managers and psychologists found themselves particularly talented for influencing other people.

Some items that varied substantially among occupations do not seem to be directly associated with job characteristics, vocational interests, or daily tasks; instead, they may rather reflect an individual's broader worldview (e.g., "Support liberal candidates," "We should be tough on crimes") or even emotional tendencies (e.g., "Tend to feel very hopeless"). For example, perhaps unsurprisingly, religious professionals were the least supportive of liberal views on average, whereas incumbents of various creative occupations as well as lawyers tended to hold the most liberal views.

Figure 6

Hypothetical Trait Distributions of the 10 Lowest- and 10 Highest-Scoring Occupations for Big Five, Based on the Mean and Standard Deviation Values From Tables 4–8



Note. The figure also illustrates the findings that higher scoring jobs were somewhat less homogenous in openness, similarly to emotional stability, extraversion, and conscientiousness. See the online article for the color version of this figure.

Clustering of Occupations by Personality Profiles

Using MDS, we transformed the multidimensional 4d personality profiles into a simpler two-dimensional form, separately analyzing domains and nuances. The clustering of the occupational groups aligned with the overall ISCO structure, with more narrowly defined 4d groups generally coalescing within the same broader ISCO groups. However, there were several exceptions, some at least not counterintuitive. For instance, photographers and audiovisual technicians, classified as technician and associate professional roles in ISCO, had average personality profiles similar to creative professions, indicating a potential overlap in creative characteristics and tasks. Likewise, travel guides, categorized as service workers in ISCO, showed more similar personality profiles to (language) teachers and public relations professionals, suggesting shared psychological traits among them and positioning them further from other service workers.

Managerial positions tend to cluster together with lower average neuroticism and agreeableness but higher conscientiousness and extraversion compared to the overall means of these variables, yet there was noticeable variation along the openness-related axis. For example, advertising and public relations managers were positioned quite distantly from retail managers. Likewise, teachers and educators varied noticeably along the openness axis, with those teaching at higher levels (university, secondary education) scoring higher than those teaching at primary schools, vocational schools, or nurseries.

Cross-Validation of the Findings

To ensure that our findings were neither self-report artifacts nor sample-specific, we cross-validated our self-reported results against informant reports and directly compared them to other findings. No one study can ever provide sufficient evidence for a psychological phenomenon, although very large and methodologically rigorous studies such as ours provide stronger evidence than smaller and less rigorous studies. Likewise, no single method—typically, self-reports—can provide definitive evidence because psychological constructs are unobserved and should not be confused with their particular assessments that contain other sources of variance besides the intended constructs. Where different studies and different methods provide reliably discrepant findings, these discrepancies' sources can be leveraged for new knowledge (e.g., suggesting that reputational consequences matter more for occupational sorting than identity-driven career choices) and better practice (e.g., use of informant reports in job counseling, hiring, or coaching). However, to the extent that the findings align, they provide particularly compelling evidence for the robustness of the phenomena in question.

Indeed, the correlations between occupational differences based on self-reports and informant reports were remarkably high for both domains and nuances, supporting the reliability and validity of our findings. The magnitudes of occupational differences also replicated well across methods. That is, occupational differences in personality domains and nuances did not reflect merely people's self-concepts but equally their externally visible traits—that is, their reputation. Besides supporting the findings' robustness, this may suggest that occupational differences are not especially driven by people's identity, in part uniquely reflected in their self-reports, contributing to career selection, nor reputation, in part uniquely reflected in informant reports about them, contributing to consequential decisions made about their career progression by other people. Practically speaking, this finding suggests that self-reports and informant reports can be used in job counseling, hiring, and coaching with comparable validity and that occupational sorting is not uniquely driven either by reputation or identity.

Wolfram (2023) published personality profiles for 360 occupations, using a sample approximately half the size of ours and smoothing trait scores with small area estimation and external auxiliary information derived from the O*NET job descriptions database. Comparing the occupational rankings across the two studies for 217 occupations with overlapping data, Spearman's ρ ranged from .48 to .71. This level of overlap is remarkable given the sociocultural differences (Wolfram's sample is based in the United Kingdom) and several methodological variations. As described above, there were significant discrepancies in the personality assessment approaches between the two studies. The BFI-S used in Wolfram (2023) assessed the domains with three items each, and the domain scores are substantially correlated (Lang et al., 2011); inevitably, this limited the extent to which broad and multifaceted trait domains such as the Big Five could be assessed in this study. In contrast, we assessed the domains much more comprehensively and orthogonally (for details, see additional online material folder "The Reliability and Validity of the Big Five Scores in the 100-NP" at https://osf.io/gvha8). However, the substantial associations observed between the results, despite these differences, underscore the robustness of both our and Wolfram's findings. To a considerable extent, then, occupational personality differences appear to be real phenomena that are robust to assessment methods, samples, and sociocultural specificities.

Associations With O*NET Work Styles

The available O*NET database was used to examine the relationships between the Big Five personality domains and O*NET work styles, developed based on various personality traits but not directly representing the now-common Big Five. That is, the work styles ratings did not directly represent personality trait differences among job incumbents. Moreover, the work styles were rated by a small number of experts or incumbents using a brief questionnaire, raising questions about the assessments' reliability and validity. Yet, the work styles had numerous significant correlations with the Big Five domains. Most correlations pertained to extraversion and openness, consistently with these domains varying the most across occupations (Table 2). Conversely, agreeableness, which showed the least variance across jobs, had no significant correlations with work styles.

The correlations between work styles and the Big Five domains contain notable patterns, particularly regarding leadership and integrity, that correlated with all Big Five domains except agreeableness. This aligns with previous findings that higher levels of extraversion, openness, and conscientiousness and lower levels of neuroticism are associated with enhanced work performance (Judge et al., 2013). Leadership qualities are particularly valued in managerial and leadership roles, where job performance and personality fit are critical factors in the selection process. Hence, the selection process may naturally lead to an emergence of associations between leadership and domains associated with overall higher performance. In contrast, conscientiousness had fewer correlations with work styles than expected, despite its established link with job performance. This might be due to seemingly conscientiousness-related work styles (persistence, dependability, and attention to detail) reflecting traits associated with good performance that are important at most jobs, leading to less trait-related variability between occupations than within occupations. So, the importance ratings (work styles) may not reflect the actual mean occupation-level conscientiousness.

There were also some unexpected associations, such as openness being most strongly correlated with work styles (i.e., achievement/effort, persistence) that appear more aligned with conscientiousness (Hough & Ones, 2001; Sackett & Walmsley, 2014). This could indicate conceptual differences between Big Five and O*NET work styles; again, what is expected from jobs does not always have to align with trait differences among actual people on these jobs. Furthermore, the question is less that openness *did* correlate with some seemingly conscientiousness-related work styles; the question is that these work styles did *not* correlate with conscientiousness, which may be because conscientious people are sought at every job and hence the trait's limited variations among jobs do not reflect job demands.

These findings suggest that the Big Five personality domains partially align with the O*NET work styles, and many of the correlations are intuitive, yet the two ways to map jobs psychologically are complementary rather than redundant. While work styles reflect the traits expected to enhance performance by either job incumbents themselves or experts, our data map the actual personality trait differences across occupations. Going forward, O*NET could also include information on job incumbents' typical levels of the Big Five and the personality nuances varying most with jobs.

Occupations With Higher Performance-Related Average Trait Scores Are More Selective

We also explored whether Big Five scores of occupational groups were more homogeneous at the higher (or lower, for neuroticism) end of the mean scores. This hypothesis was drawn from intelligence studies, where job groups with higher mean intelligence levels tend to have lower variance in these scores than groups with lower mean levels (Harrell & Harrell, 1945; Jensen, 1980; Wolfram, 2023). In other words, we expected more homogeneity in those personality traits that are generally linked with better job performance in jobs having higher average levels of these traits. The majority of our findings supported this hypothesis, particularly for extraversion and conscientiousness. These results align with the earlier findings, where conscientiousness and extraversion have the strongest associations with better job performance (Judge et al., 2013; Wilmot & Ones, 2021). Self-reported scores revealed expected correlations for neuroticism and openness, confirming that lower neuroticism and higher openness are often associated with enhanced job performance and are, therefore, likely more selected for in jobs demanding these traits. For agreeableness, the expected correlation appeared only in informant-reported data. However, in combined self-ratings and informant ratings that may provide the most reliable mean and variance estimates, all hypothesized correlations were statistically significant, ranging from .20 s for neuroticism, openness, and agreeableness to .40 s for extraversion and conscientiousness.

Wolfram (2023) found a partly similar pattern of correlations. Specifically, neuroticism had a substantial positive relationship between means and *SD*s, while openness and conscientiousness had negative correlations. Wolfram did not find the expected relationship for agreeableness, whereas we found it in informant reports and combined self-reports and informant reports. However, the findings were more noticeably discrepant for extraversion—it unexpectedly had a positive mean–*SD* correlation in Wolfram's study, whereas in our study, the correlation was consistently negative, as expected. Wolfram reported potential floor and ceiling effects in the trait score distributions given their limited assessment, which could bias the results, but this may not fully account for the observed discrepancy with our study. One explanation may lie with differences in assessing personality traits. The three extraversion items in the BFI-S used in Wolfram exclusively tap sociability (e.g., "Is talkative"; "Is outgoing"; "Is reserved"), while our findings suggest that the assertiveness component of extraversion ("Want to be in charge") may vary equally between occupations. This suggests potential variability in the content of the extraversion domain between the studies. Sociocultural differences and job expectations might be another influencing factor, possibly indicating a higher selection for extraversion in Estonia compared to the United Kingdom.

Using partial correlation analyses, we found that high-performance indicators such as income and SIOPS prestige scores played a role in the mean–*SD* relationship for openness within occupational groups. When accounting for these variables separately, the mean–*SD* correlation for openness diminished. This suggests that these nonpsychological variables account for a substantial part of the observed relationship between the mean and *SD* for openness. The mean–*SD* correlations for other traits, however, remained unaffected, suggesting that something not captured by prestige and income levels made jobs with high extraversion, and to a lesser extent, emotional stability, agreeableness, and conscientiousness, less variable in these traits.

Implications for Personality Science

Among personality trait research's main justifications and implications are the traits' associations with consequential life outcomes. When these outcomes involve self-reported psychological constructs such as life satisfaction or gratitude, the associations can range up to $r \approx .50$ but are more commonly in the range of $r \approx .10$–$.30$ (e.g., the associations in the data reported in Soto, 2019). With more objective outcomes characterizing specific choices, achievements, health conditions, or behavior patterns, the associations are usually considerably smaller (e.g., Seeboth & Mõttus, 2018); for example, in the mega-analysis of Beck and Jackson (2022), all associations were smaller than $r < .05$. Given this, occupational choice can be considered a life outcome that has some of the strongest correlations with personality traits (e.g., $\eta^2 = .07$ means $r = .26$ and $\eta^2 = .04$ means $r = .20$). So, our findings affirm the importance of personality traits in consequential life outcomes.

Among the Big Five domains, conscientiousness, neuroticism, and extraversion stand out as the outcomes most often discussed in relation to life outcomes. Higher levels of conscientiousness, for example, relate to various health variables (Jackson et al., 2015; Wright & Jackson, 2022), better job performance (Judge et al., 2013; Wilmot & Ones, 2021), and socioeconomic outcomes (Prevoo & ter Weel, 2015). Conversely, neuroticism is associated with decreased life satisfaction (Anglim et al., 2020; Mõttus et al., 2024), increased incidence of psychopathology (Wright & Jackson, 2022), mental health issues (Kang et al., 2023), and challenges in relationships (Donnellan et al., 2005), while extraversion often has association patterns that inversely mirror those of neuroticism. In contrast, agreeableness and openness tend to be less often discussed in relation to life outcomes, apart from antisocial behavior (Jones et al., 2011) and political preferences (Sibley et al., 2012). However, our findings emphasize the particular importance of openness in one other major life domain—career path. This finding is supported by prior research on occupational interests (Hurtado Rúa et al., 2019) and occupational sorting (Törnroos et al., 2019; Wolfram, 2023). Furthermore, the comparatively strong positive correlation between openness and educational attainment (Beck & Jackson, 2022; Mõttus, Realo, et al., 2017) is in line with this finding, since occupations tend to be clustered along educational attainment. Yet, neither the education–openness overlap ($r \approx .17$ in Mõttus, Realo, et al., 2017; $r \approx .05$ in Beck & Jackson, 2022) nor the openness–intelligence overlap ($r \approx .17$ in Anglim et al., 2022) are strong enough to account for the trait's variation across occupations.

Our study also contributes to the understanding of person–environment transactions by showing that these may not always be equally distributed across trait levels. Some jobs may come with increased homogeneity, particularly in relation to traits such as extraversion and conscientiousness, but also other performance-related traits. This could be attributed to selection effects, implying that specific trait levels are either particularly sought after or particularly strongly gravitate toward certain occupations, making these occupational groups more uniform; selection and attraction to other jobs may be driven by other factors, including happenstance. Another potential mechanism is that professions demanding higher levels of certain performance-related traits might foster further growth in these very traits, in line with the corresponsive principle of personality development (Le et al., 2014; Roberts et al., 2003). Future research will show if there is also evidence for such differential person–environment transactions in other life domains.

Finally, our findings also provide a further piece of evidence that informant reports are at least as valid a method for personality assessment as self-reports (Connelly & Ones, 2010). There is a pressing need for the field to move beyond confusing unobserved constructs with their single assessments, which typically mean self-reports (McCrae & Mõttus, 2019). These findings again show that informant reports provide a particularly good complementary personality assessment method that can be used at a large scale for assessing almost any trait. In particular, the combination of the two assessment methods can provide particularly valid findings, helping to disentangle single-method biases and true traits (e.g., Mõttus et al., 2024).

Practical Implications

The primary applications of personality trait research include career counseling, coaching, and applicant selection because a match between individuals' and jobs' attributes can contribute to various desirable outcomes (Kristof-Brown et al., 2005; Törnroos et al., 2019; van Vianen, 2018). These activities assume that occupations vary in personality traits that are typically required for being successful in them. Given that incumbents' traits likely provide good approximations to traits typically expected at a job (although there may be exceptions, as our analyses pertaining to O*NET work styles show), our study is one of the first to empirically test the *extent to which* this assumption holds across a broad range of occupations and the first to do this with a comprehensive and multimethod personality assessment. Our findings that occupations do vary along the Big Five personality domains and, especially, narrower personality nuances broadly support this assumption but also provide a more detailed answer.

First, while occupations do differ in average trait scores and many occupations do have distinctive personality profiles with at least one Big Five domain having an average score that is noticeably different from the population mean, many occupations do not have a distinctive trait profile. For example, 57% of the 263 jobs we mapped in personality traits had all average Big Five domain scores within 0.3 *SD*s from the population mean. Occupations' mean trait scores are normally distributed like those of individual people, although the distributions are narrower for occupational means. This complicates finding a specific personality–job fit for many jobs and many people. In these circumstances, more viable targets may be identifying people with atypical trait profiles who are *less* likely to be a good fit for jobs with nondistinctive incumbent profiles (e.g., in applicant selection) or identifying jobs with distinctive incumbent trait profiles that may *not* be a good fit for people with a nondistinctive trait profile (e.g., in counseling or coaching).

Second, attempts to match individuals and jobs based on the Big Five personality domains could prioritize openness and extraversion because these domains vary the most with occupations. Third, it may often be more useful to use narrower traits such as personality facets or, especially, nuances for matching people and jobs because jobs differ more in certain narrower traits than in domains, as is common for many other life outcomes (e.g., Stewart et al., 2022). This is most readily doable when developing algorithms for matching people and jobs. For example, applications that recommend suitable occupational choices based on individuals' trait ratings or other sources of information about their traits may provide more accurate advice when relying on selected narrower traits that vary most among jobs in our data rather than on the Big Five domains. Although not intended as a job counseling tool, we have already created an application that allows interested people to explore how their personality traits compare to those of various job incumbents; this application leverages the personality nuances outlined in this study (https://apps.psych.ut.ee/JobProfiler/). Fourth, it may be particularly useful to find personality-wise matching people and coach for jobs that typically require higher levels of extraversion, conscientiousness, emotional stability, openness, and agreeableness (or nuances within these domains), as jobs with higher average levels of these traits tend to attract and retain particularly homogeneous incumbents. Often, these jobs likely include more prestigious ones with higher expectations and more stringent candidate selection procedures. Fifth, our findings suggest that both self-reports and informant reports can be used with comparable validity in job counseling, hiring, and coaching.

Successful job counseling, coaching, and applicant selection also depend on having publicly available data that reliably characterize a broad range of occupations in personality traits. While private companies may already have such databases, they may not be publicly accessible for the common good (e.g., to job counselors). Likewise, the validity of the privately held and thus unscrutinized data could be tested by comparing them against publicly available data. Our findings provide the most comprehensive yet public and easily accessible database (https://apps.psych.ut.ee/JobProfiles/) on the Big Five scores of a broad range of occupations that can be used by job counselors, coaches, and HR workers, among others. The public availability of such data may also lower the entry barriers for companies aiming to offer personality-based selection, counseling, or coaching services, helping them to compete against established companies who may privately hold similar data.

However, it is essential to recognize that these data are about mean differences between occupations, while many individuals defy these mean-level trends (see Figure 6). So, while personality assessments can provide one valuable piece of information about person–job fit, they should always be complemented by a comprehensive understanding of each individual's distinct attributes and potential. Several other factors, such as cognitive ability and mental health (Wolfram, 2023), bodily features, interests (Hoff et al., 2020), and external facilitators and constraints, among others, can influence occupational sorting—besides mere happenstance.

Future Directions

Among possible future research directions, we see a need for a global public-domain database that describes typical trait levels of hundreds of jobs, using both the Big Five and narrower traits. It would be particularly useful if the trait profiles could be stratified by the region or country of interest, demographic variables, and incumbents' happiness with their jobs and length of incumbency; for example, typical personality trait levels of job-satisfied and long-term incumbents may be especially useful for estimating which jobs best fit for which people. It is also possible that personality traits typical to some jobs vary meaningfully across cultures. Such a database could be used worldwide for job counseling and personality-based occupational services.

Future research could also use machine learning models based on personality domains or nuances to increase the accuracy of matching individuals to suitable occupations based on their distinctive trait profiles (cf. Mõttus et al., 2020). For example, we do not know yet how accurately we could predict one's job from their trait profile if we build bespoke models for each job, and for which jobs this accuracy could be particularly high. The higher this accuracy, the likelier it is that personality trait assessments and predictive models based on these can be used to match people with jobs that are psychologically suitable for them. Provided that this accuracy is sufficiently high, it will be possible to develop algorithms that automatically identify jobs that are more and less likely to correspond to one's trait profiles. Also, future empirical research should further investigate the mechanisms of personality occupational sorting, including the role of familial cotransmission of personality traits and other attributes such as job choice (Buser et al., 2023; Kandler et al., 2011).

Limitations

A limitation of our study was sole reliance on self-reported occupation titles and lacking detailed job descriptions. This occasionally hindered the accurate categorization of atypical responses under ISCO categories, as accuracy in this requires knowledge of the principal tasks and duties of each occupation. This lack of detailed information may have led to some inaccuracies in the classification process and therefore possibly underestimation of some occupational differences. Furthermore, it would have been ideal to be able to link participants' personality ratings to their tax and other government records on their job status. However, a large majority of the self-reported responses could be categorized straightforwardly, and we do not currently have a strong reason to believe that people systematically misreported their jobs. Moreover, the creation of distinct, self-created groups for ambiguously named occupations likely mitigated the impact of this limitation. We note, however, that the inclusion of these self-generated job titles did not change our main findings, and these titles can be filtered out from the findings, including in our interactive application.

While we captured a wide array of occupations, we excluded several occupational groups due to small sample sizes; these included physicists, dancers/choreographers, fashion models, athletes, and legislators, among others. The absence of these groups could potentially influence the estimated magnitudes of differences and affect the results of our homogeneity analyses as well. Also, it should be acknowledged that some occupations that we did include had small sample sizes (yet, even our smallest samples were larger than the median sample used for O*NET job style ratings). Although the smoothing procedure mitigated this limitation as estimates based on small samples were nudged toward those of much larger samples, future research should aim to replicate the personality profiles, especially for the smaller groups. Moreover, while we controlled for gender in the main analyses, it should be noted that the overall sample had significantly more women than men, which could also affect the generalizability of the results. Yet, the consistency between our findings and those of Wolfram (2023), which were based on more gender-balanced samples, somewhat mitigates this concern.

In addition, the findings' generalizability may be limited due to our reliance on a sample drawn from Estonia. However, the results were similar to those from a British sample and tracked with many O*NET work styles originating from the United States, so at least broad patterns in the findings generalize to other liberal Western democracies with industrialized free market economies, such as Estonia. Yet more work with diverse samples representing many world regions is required to establish the universals and specifics of how personality varies with jobs.

Conclusion

While work plays a pivotal role in many individuals' lives and personality traits are important in occupational sorting, there is a lack of research to map personality differences across various occupations. Bridging this gap, we estimated the extent to which personality traits differ between jobs and provided the Big Five domain and narrower nuance profiles for 263 occupational groups. We also showed that jobs do not only differ in mean trait levels but also in how consistently incumbents (have to) match these levels, with those working in jobs with higher levels of performance-related traits often being more similar to one another. Notably, our main results based on self-reports aligned well with those based on informant ratings and those found in a previous study, reaffirming the validity and robustness of our findings. Jobs' average trait scores were also tracked with widely known O*NET work style ratings, supporting the validity of these as much as the validity of the personality trait rankings. We provide an interactive application for in-depth examination of occupational personality profiles. This comprehensive work establishes a basis for future investigations and has practical applications in career counseling, recruitment, and vocational psychology.

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Received October 18, 2023
Revision received September 17, 2024
Accepted September 17, 2024 ■