How satisfaction varies among 263 occupations

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Abstract

Despite theoretical reasons to think that occupation plays a role in life satisfaction (LS), empirical evidence on the association is surprisingly limited. Moreover, because LS closely tracks personality traits, not controlling for these has left the existing results inconclusive. In pre-registered analyses, we examined occupational differences in LS and job satisfaction (JS) among 59,000 Estonian Biobank participants who represented 263 occupations, controlling for demographic variables and comprehensively assessed personality traits. Jobs differed in LS and JS before (η^2 = .05 and η^2 = .07, respectively) and even after adjusting for all covariates (η^2 = .01 to .02 and η^2 = .06, respectively). Various medical professionals, psychologists, special needs teachers, and self-employed tended to have the highest LS levels, whereas security guards, survey interviewers, waiters, sales workers, mail carriers, carpenters and chemical engineers tended to score the lowest. Jobs with the highest JS included religious professionals, various medical professionals, and authors, while kitchen, transport, storage and manufacturing labourers, survey interviewers, and sales workers were among the least satisfied with their jobs. Exploratory analyses suggested that income and O*NET-derived job characteristics, such as interest orientations like realistic, enterprising, and conventional, could explain some of the satisfaction variance among occupations. We conclude that occupation ranks among satisfaction's strongest correlates, besides, and partly net of, personality traits.

Keywords: life satisfaction, job satisfaction, personality, occupation, well-being

Introduction

Life satisfaction (LS) refers to individuals' overall assessments of their lives (Diener, 1984). It is a key psychology construct, and an end unto itself for many people. The strongest predictors of its variance among people are personality traits (Anglim et al., 2020). For example, after accounting for measurement error and single-method biases, LS could be predicted with nearly $r = .80$ accuracy from the trait domains of neuroticism, extraversion and conscientiousness, within and across samples (Mõttus et al., 2024), and these associations mostly reflected shared genetic mechanisms (Mõttus et al., 2025). Moreover, more specific trait nuances, such as feeling misunderstood, unexcited, indecisive, bored or unrewarded provided a predictive accuracy of nearly $r = .90$ (Mõttus et al., 2024). Yet, about 20% of the variance in LS has remained unexplained by personality traits, so other factors must also play some role.

For example, there are small age and gender differences in LS (Andrade et al., 2019; Blanchflower & Oswald, 2008; Graham & Ruiz Pozuelo, 2017; Rajani et al., 2019). Also, higher education (Cheung & Chan, 2009), income (Ngamaba et al., 2020; Tan et al., 2020), health (Geerling & Diener, 2020), and being employed (McKee-Ryan et al., 2005) and in a romantic relationship (Geerling & Diener, 2020) can each explain a fraction of LS variance, usually less than 5%. To some extent, however, these associations may have been confounded by personality traits, which robustly correlate with a range of life outcomes (Soto, 2019), besides LS. This is consistent with the personality correlates of LS similarly correlating with how satisfied people are with their career choice, income, health, relationships and other life domains (Mõttus et al., 2024). Recent life events may also explain some of LS variance. For example, meta-analytic estimates suggest that graduating, starting a new relationship or career, and breaking up can each account for between 0.1 and 3% of LS's variance, although at least some of these effects could recede over time (Bühler et al., 2023).

Moreover, most adults spend much of their lives working, and jobs vary greatly in their demands and opportunities. Accordingly, there is evidence that occupational role could be associated with LS generally and job satisfaction (JS) more specifically. For example, Hofmann et al. (2018) found that relatively broad occupational groups ($k = 9$) explained 4% of the variance in LS, while skill levels explained 2% of the variance after controlling for age and sex. Törnroos et al. (2019) reported that broad occupational groups explained about 1% of the variance in JS. We have summarized studies that have reported LS or JS associations with occupational groups in Table 1.

Table 1

Summary of Studies Reporting Associations Between LS, JS, and Occupations

Reference	Study design	Main results about occupational differences	Other included/control variables
Andrade & Westover (2020)	*N* = 18,716; 2015 wave of the International Social Survey Programme, across 37 countries. Occupations: 10 major ISCO groups (1-digit codes). JS was measured using a single-item indicator.	Managers and professionals reported the highest mean JS, whereas elementary occupations, plant-machine operators, and clerical support workers reported the lowest JS.	Age, gender, education, marital status, family size, work-life balance, intrinsic and extrinsic rewards, organizational characteristics.
Easterlin et al. (2011)	*N* = 278,715; Gallup World Poll, (2005–2008; across 80 countries). Occupations: broad occupational groupings - white collar, business owner, service worker, non-farm manual worker, and farmer. LS was measured using a single question.	Differences in LS across occupations correlated with income and education levels, with white-collar workers reporting the highest LS, followed by service workers, business owners, and non-farm manual workers. The patterns of LS across occupations differed slightly between developed and less developed countries.	Age, gender, marital status, income, education level, and urban-rural residence.
Georgellis et al. (2022)	*N* = 13,664 individuals, who were followed on average 5 waves; British Household Panel Survey (BHPS) data (1996–2008). Occupations: status scores measured by CAMSIS (Cambridge Social Interaction	Men in high-status occupations reported higher LS, while those in middle-status jobs had lower LS than both high- and low-status groups. For women, occupational status had a weaker positive effect on LS. Income partially explained	Age, marital status, children, hours worked, firm size, job sector, and income.

Reference	Study design	Main results about occupational differences	Other included/control variables
	and Stratification Scale), ranging from 0 to 100. LS was measured using a single question.	these effects but did not fully account for them.	
Hessels et al. (2018)	*N* = 50,908; Gesis Eurobarometer data (across 28 countries). Occupations: white- and blue-collar, and high- and low-skilled workers were distinguished based on major ISCO groups (1-digit codes). LS was measured with a single item.	Self-employed individuals consistently reported higher LS than paid employees, even within similar occupations matched by collar type and skill level.	Gender, age, marital status, number of children, education level, perceived financial situation, and perceived job situation.
Hofmann et al. (2018)	*N* = 1,140; representative sample of the Swiss workforce. Occupations: 9 major ISCO groups (1-digit codes) and low/high skill groups. LS was measured with the German version of the 5-item Satisfaction with Life Scale (Diener et al., 1985).	Occupations with higher skill levels, such as managers and professionals, reported being more satisfied with their lives compared to the average across all occupational groups. The lowest mean scores for LS were among elementary occupations, plant and machine operators, and clerical support workers.	Sex and age.
Ravina-Ripoll et al. (2021)	*N* = 2,972; Spanish Sociological Research Center study. Occupations: (1) fixed-salary employees, (2) temporary employees, (3) entrepreneur or professional with employees, and (4) professional or self-	Entrepreneurs with employees were the happiest. Those with higher education and top incomes reported the greatest happiness.	Sex, education, and income.

Reference	Study design	Main results about occupational differences	Other included/control variables
	employed worker without employees. LS was measured using a single item "Generally, to what extent do you consider yourself a happy or unhappy person?".		
Seiler Zimmermann & Wanzenried (2019)	*N* = 4,295; Swiss Household Panel data. Occupations: managers vs non-managers. LS and JS were both measured using single items.	Managers reported higher LS, JS, and financial satisfaction compared to non-managers. The positive effect of management positions on LS was stronger for men but still significant for women.	Misqualification, age, nationality, health status, education, household income, living with a partner, children in the household, and work-life interference.
Törnroos et al. (2019)	*N* = 22,787; BHPS and UK Household Longitudinal Study. Occupations: 25 broad occupational groups. JS was measured using a single item. Personality traits were assessed using a 15-item Big Five inventory (Gerlitz & Schupp, 2005).	Occupations explained 1% of the variance in JS. A better fit between individual personality and the average occupational personality was associated with increased JS, particularly in the case of neuroticism and openness.	Sex, age, study (data source), and Big Five personality traits.

These studies suggest that individuals in higher-status occupations generally report greater satisfaction than those in lower-status roles. Additionally, several studies (e.g., Hessels et al., 2018; Ravina-Ripoll et al., 2021) have found that self-employed individuals report higher satisfaction than paid employees, even within occupations of similar status or skill level. Recent meta-analytical findings by Stephan et al. (2023) further support the overall higher well-being of entrepreneurs.

Income have been one of the main factors that tracks jobs typical satisfaction levels (Navarro & Salverda, 2019; Ng & Diener, 2014; Ngamaba et al., 2020; Tan et al., 2020), although the relationship may be non-linear and moderated by gender (e.g., Georgellis et al., 2022), and dependent on social comparisons (Bárcena-Martín et al., 2017; Easterlin, 1974). Besides earnings, other specific features of occupations may influence satisfaction. According to the widely used Job Characteristics Model (Hackman & Oldham, 1976), five distinct features—skill variety, task identity, task significance, autonomy and receiving feedback—could be relevant. These characteristics may positively influence the perceived meaningfulness of the job, sense of responsibility for outcomes and awareness of the results, all of which are associated with work motivation and satisfaction (Bakker & Demerouti, 2017). In addition, satisfaction can be reduced by some job-related stressors (Ritter et al., 2016), alongside poor person-environment fit (Hoff et al., 2020; Kristof-Brown et al., 2005; Törnroos et al., 2019), although this evidence is inconsistent yet (e.g., Tsabari et al., 2005; Wiegand et al., 2021; Wille et al., 2014).

However, besides being scarce, existing evidence to suggest that occupation could explain some variation in LS and JS is weakened by two major caveats. First, the relationships could be partly or even fully confounded by personality as these are both correlated with LS and JS (Mõttus et al., 2024) and vary between jobs (Anni et al., 2024). Yet, personality traits have generally not been controlled for in studies investigating the links between LS and JS and occupational role, although there are exceptions (e.g., Törnroos et al., 2019). Second, to date most evidence about the differences in LS and JS between occupations is limited to a small number of broad occupational categories, such as white collar workers (e.g., Easterlin et al., 2011; Navarro & Salverda, 2019), managers (e.g., (Ravina-Ripoll et al., 2021; Seiler Zimmermann & Wanzenried, 2019) or the self-employed (Hessels et al., 2018; Stephan et al., 2023). While some studies include a wider selection of occupational categories (e.g., Andrade et al., 2019; Hofmann et al., 2018) or status-based divisions (Georgellis et al., 2022), even these groups encompass many distinct jobs. Above-outlined job characteristics that contribute to satisfaction, such as skill variety, task significance, and autonomy (Hackman & Oldham, 1976), vary significantly across specific occupations, regardless of industry, seniority, or job type. Hence, although collapsing jobs into broad categories may help with statistical power in small samples, it likely masks occupational differences in satisfaction. Besides the availability of specific job titles, comparing numerous occupations requires very large samples for each occupational group to be sufficiently represented (Anni et al., 2024).

Our main objective was to explore the variability of LS and JS among 263 specific occupations, using a very large sample (N = 69,303) that covered about 7% of the Estonian adult population. Besides high statistical power and population representativeness, we also improved on past research by mapping the satisfaction across a broad range of specific occupations. Moreover, we controlled for comprehensively assessed personality traits (Big Five domains and nuances that vary most across occupations), besides demographic factors. In addition to these pre-registered analyses of occupational variability in satisfaction, we conducted several exploratory analyses. First, we considered income as a moderating factor in the relationship between occupations and LS/JS (Bhardwaj et al., 2021; Ngamaba et al., 2020; Tan et al., 2020). Second, we explored how job-level satisfaction scores relate to numeric job characteristics available in the O*NET database (such as interests and values) and to occupational prestige scores, to better understand which job features may be linked to higher or lower satisfaction among incumbents. To our knowledge this is the most comprehensive and rigorous study yet on satisfaction differences among jobs.

Method

The activities of the Estonian Biobank (EstBB) are regulated by the Human Genes Research Act, adopted in 2000. Individual level data analyses were carried out according to the approval 1.1-12/626, 13.04.2020 granted by the Estonian Committee on Bioethics and Human Research (Estonian Ministry of Social Affairs), using data according to EstBB release application 3-10/GI/11571.

The data are part of a large, ongoing biobank study and therefore cannot be made publicly available. However, researchers may request access through an application process via the Estonian Biobank (https://genomics.ut.ee/en/content/estonian-biobank). The main analyses were pre-registered (osf.io/c84dh, Vainre & Anni, 2024). The R (version 4.3.1; R Core Team, 2023) code used for the analyses is available at: https://osf.io/sqj3c/files/osfstorage?view_only=bc6649e31254419da5a7470077794129d.

Recruitment, sample size and eligibility criteria

Participants were members of the public ("gene donors") who had donated their blood to the EstBB and enrolled in the EstBB personality study second cohort (Milani et al., 2024; Vaht et al., 2024). As part of the cohort recruitment, data used in this study were collected via an online survey between November 2021 and April 2022, with e-mail invitations sent to 182,405 gene donors. To encourage participation, the study was widely advertised in conventional and social media and participants were offered feedback on their Big Five personality scores. We included everyone who (a) had completed the survey assessing LS, JS and personality traits in Estonian and with no more than 10 missing responses and (b) belonged to occupational group with at least 25 participants (Anni et al., 2024).

Participants

The original dataset contained 80,769 participants. After excluding participants based on eligibility criteria described above, there were 69,303 participants in the dataset. Where the occupation was held by more than 1,000 participants, we randomly sampled 1,000 participants from this sub-group. So, the effective dataset we analysed was N = 59,042 (age M = 47.57, SD = 14.57, *Mdn* = 47, range from 18 to 102). Other descriptive statistics are presented in Table 2.

Table 2

Descriptive Data

Variable		Total N	Sub-group N (%)
Sex	Female	59,042	41,176 (69,7%)
	Male		17,866 (30,3%)
ISCO 4-digit occupations		59,042	
Education	Primary or without primary	59,042	94 (<1%)
	General lower secondary		1,720 (2,9%)
	Vocational lower secondary		1,772 (3,0%)
	General or vocational upper secondary		14,405 (24,4%)
	Tertiary vocational		6,793 (11,5%)
	Bachelor's or equivalent		14,598 (24,7%)
	Masters's or equivalent		18,498 (31,3%)
	Doctorate or equivalent		1,162 (2,0%)
Life satisfaction		59,024	
Job satisfaction		58,905	
Neuroticism		59,024	
Extraversion		59,024	
Openness		59,024	
Agreeableness		59,024	
Conscientiousness		59,024	

Variables

Life satisfaction

LS was measured using three items rated on a six-point scale ranging from *very inaccurate* to *very accurate*. The items included ratings for happiness with life, lack of direction (reverse coded), and having a dark outlook on the future (reverse coded). As evidence of its validity, the aggregate of these items correlates $r > .90$ with the Satisfaction with Life Scale (SWLS, Diener et al., 1985) and an aggregate of eight diverse domain satisfaction items (Mõttus et al., 2024).

Job satisfaction

JS was a composite of two ratings. Satisfaction with (a) job and (b) choice of profession were each measured with one item each, using the same six-point scale (*very inaccurate* to *very accurate*), and correlated highly, $r = .62$ ($p < .001$). We averaged their standardised scores.

Occupation

Occupation was captured as free text and coded according to the latest International Standard Classification of Occupations (ISCO-08; International Labour Office, 2012). Here, we used the finest, four-digit, classification of occupations. Additionally, for a few groups ($k = 26$) where categorisation was not possible due to the overly generic job title description provided by participants in their free text response, we created bespoke codes based on one-, two-, or three-digit category levels. This approach is detailed elsewhere (Anni et al., 2024). In total, our sample covered 263 occupations with at least 25 participants.

Personality traits

The Big Five personality domains were assessed using 60 items from the 100 Nuances of Personality item pool (Anni et al., 2024; Henry & Mõttus, 2023). The items were responded to using the same six-point scale as satisfaction items. The Big Five scores had high test-retest reliability, discriminant validity (orthogonality), convergent validity with other Big Five scales, and they correlated meaningfully with various criterion variables (Anni et al., 2024). Moreover, the scores explained more variance in other Big Five scales than vice versa, providing evidence of their superior comprehensiveness. We also considered 21 specific personality nuances that had previously shown the most variability between occupations (Anni et al., 2024). Personality nuances are specific personality traits with trait properties, operationalised with single test items (Condon et al., 2020). For example, personality nuances varying the most among jobs—and more than the Big Five domains—included items such as “Want to be in charge”, “Like to solve complex problems”, and “Have a natural talent for influencing people”.

Income

Personal income was measured by a single question “what is your personal monthly net income on average” captured as a free text. We included the participants whose reported incomes ranged from 100 to 100,000 euros (N = 54,794). The income values were rank transformed for further analysis to reduce the influence of extreme values and skewed distribution.

Prestige

The Standard International Occupational Prestige Scale (SIOPS; Ganzeboom & Treiman, 1996) scores were derived using the DIGCLASS package (version 0.0.1; Cimentada et al., 2023), which converts ISCO-08 codes into various social class variables. All four-digit ISCO-08 codes were directly converted. For groups with bespoke codes, the corresponding two-digit parent group codes were used for conversion.

Additional occupational characteristics

We derived some potential occupational characteristics from the Occupational Information Network (O*NET; Peterson et al., 2001), developed by the U.S. Department of Labor. From among various O*NET job-level characteristics, we focused on Work Values and Interests ratings. The O*NET’s six Work Values—Achievement, Autonomy, Recognition, Relationships, Support, and Working Conditions—describe the job's nature and the work environment's conditions. Values are defined as broad aspects of work consisting of specific needs that are important for a person's satisfaction, as outlined in the Theory of Work Adjustment (Lofquist & Dawis, 1984). The ratings indicate the extent to which an occupation fulfils each specific Work Value. The O*NET's Interest dimensions are based on Holland’s model of personality types and work environments (Holland, 1997). As a result, interest profiles consist of ratings that describe work environments across six “RIASEC” categories: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional.

Statistical analyses

Handling variables

To match the O*NET occupational codes with ISCO-08 codes, we used the crosswalk provided by the European Commission (available at https://esco.ec.europa.eu/en/use-esco/other-crosswalks). Where multiple O*NET occupations corresponded to a single ISCO-08 four-digit code, we calculated the mean rating for that ISCO code. This allowed us to derive O*NET ratings for 213 out of the 263 occupations for which we had mean LS, JS and personality trait scores.

Handling missingness

We had a very small amount of data missingness. LS and personality traits had 18 missing values (0.03%) out of 59,024 participants. JS had 137 missing values (0.23%). The missing responses of each personality trait was replaced by the median of that item prior to calculating Big Five personality scores. Where demographic as well as LS and JS variables were missing, the participants were excluded from the model that required that variable.

Statistical analysis

We used R (version 4.3.1; R Core Team, 2023) in RStudio (Posit Team, 2022) for statistical analysis. The following packages were used: dplyr (version 1.1.4; Wickham et al., 2023), stringr (version 1.5.1; Wickham, 2009), here (version 1.0.1; Müller, 2020), readr (version 2.1.5; Wickham et al., 2015), tidyr (version 1.3.1; Wickham et al., 2024), purr (version 1.0.4; Wickham & Henry, 2025), flextable (version 0.9.3; Gohel & Skintzos, 2023), car (Fox & Weisberg, 2018), MOTE (version 1.0.2; Buchanan et al., 2019), lmerTest (Kuznetsova et al., 2017), ppcor (version 1.1; Kim, 2015), rempsyc (version 0.1.6; Thériault, 2023), and DT (version 0.28; Xie et al., 2023).

We fit several general linear models, with either LS or JS as the dependent variables (i.e., two separate lines of modelling). In all models, the four-digit occupation code was the independent variable with *managers* set as the reference category. The models differed in the covariate variables. Working incrementally, we were interested in the change in the *eta-squared* (η^2; percentage of explained dependent variable variance, conditional on other covariates) as we added more covariates to the models. We first used sex, age, and age^2 as covariates. We then added education, and finally the Big Five personality domains as covariates. Additionally, instead of the Big Five domains, we controlled for the 21 personality nuances varying the most among jobs according to Anni et al. (2024). Thus, there were four

GLMs fitted for the two dependent variables, that is eight in total. To account for multiple comparisons, we applied the Holm-Bonferroni correction to the p-values.

Occupational group-level LS and JS scores can be influenced by variability in group sizes, with smaller groups yielding less stable estimates. To reduce the potential noise and sampling bias associated with small occupational groups, we applied a smoothing procedure like the one used in our previous work on occupational personality profiles (Anni et al., 2024) to occupations’ mean LS and JS levels.

We smoothed the means of each four-digit ISCO occupational group toward the corresponding means of their parent group (typically the three-digit ISCO group), using weighting procedure similar to Bayesian approach. In this approach, the observed four-digit group mean was treated as the data, and the parent group mean as the prior. The smoothed value was calculated as a weighted average of the two:

$$m_{posterior} = \frac{w_{prior} \times m_{prior} + w_{data} \times m_{data}}{w_{prior} + w_{data}}$$

The weight assigned to the data increased with the group size, calculated as:

$$w_{data} = \frac{n^2}{25}$$

where *n* is the number of individuals in the four-digit group, and $w_{prior} = 25$ was fixed. This rule ensured that smaller groups were adjusted more heavily toward their parent group means, while larger groups retained their observed values. Anni et al. (2024) demonstrated that the smoothing only somewhat influenced estimates of smaller groups, making them less conservative by bringing them in line with reasonable expectations.

Changes to the pre-registered analysis plan

To improve comparability and interpretability, we used T-scores for LS and JS instead of unstandardized scores. This only changes the metric of effects sizes and is irrelevant to inferential statistics. The smoothing of means was also not pre-registered.

Results

How much did LS vary among jobs?

There were meaningful differences in LS between occupational groups. Of the three models tested, the model that included all preregistered variables (occupation, sex, age, education, and the five personality domains) performed best ($F(277, 58746) = 180.3$) with considerable differences in R^2 (change from .05 to .46; Table 3). Including education to the initial model reduced the variance in LS explained by the four-digit ISCO occupational groups from $\eta^2 = .05$ (95% CI .01 to .11) to $\eta^2 = .03$ (95% CI 0 to .08). Adding personality domains reduced the LS's variance explained by occupation slightly further, with $\eta^2 = .02$ (95% CI 0 to .06). This suggests that personality traits explain part of the association between occupation and LS, but occupation still accounts for a small portion of the variance independently.

How much did JS vary among jobs?

JS differed more strongly between occupations than LS. Similarly to LS, the model that included all preregistered predictors of JS outperformed the models without personality domains (final model: $F(277, 58627) = 58.35$; Table 3). Adding education to the initial model entailed a drop in the variance explained by occupational groups from $\eta^2 = .07$ (95% CI .02 to .14) to $\eta^2 = .06$ (95% CI .02 to .12). However, the variance explained by occupations was not reduced when we added personality domains to the model $\eta^2 = .06$ (95% CI .01 to .12), suggesting personality domains did not confound the JS-occupation associations.

Occupations with the highest and lowest satisfaction levels

The occupations with highest and lowest smoothed mean LS, adjusted for demographic variables and personality traits, are listed in Table 4. The difference between the top and the bottom occupation's LS was about 7.3 T-scores, or 0.7 SDs, whereas the difference between the averages of top and bottom 10 occupations was nearly 6 T-scores. Among the occupations with the highest LS were religious and various non-doctor medical professionals, psychologists, special needs teachers and the self-employed, but also sheet metal workers and ships' engineers. Among the jobs scoring lowest in LS were some service and customer-facing jobs, such as security guards, survey interviewers, waiters, and sales workers, but also mail carriers, carpenters and chemical engineers.

Table 3

Results of Pre-Registered and Exploratory Analyses

Satisfaction domain	**Model**[a]	***F* (df)**	***p***	R^2	**AIC**	η^2	95% CI[c] **lower**	**upper**
Life	Model 1: occ + sex + age	12.48 (265, 58758)	< .0001[b]	.05	436,873.70	.05	.01	.11
	Model 2: occ + sex + age + educ	13.14 (272, 58751)	< .0001[b]	.06	436,633.77	.03	.00	.08
	Model 3: occ + sex + age + educ + dom	180.30 (277, 58746)	< .0001[b]	.46	403,815.07	.02	.00	.06
	Model 4a: occ + sex + age + educ + dom + income	169.10 (278, 54498)	< .0001	.46	374,295.16	.01	.00	.06
	Model 4b: occ + sex + age + educ + nuances	232.57 (298, 58714)	< .0001[b]	.54	394,080.73	.01	.01	.02
Job	Model 1: occ + sex + age	18.80 (265, 58639)	< .0001[b]	.08	422,209.73	.07	.02	.14
	Model 2: occ + sex + age + educ	18.51 (272, 58632)	< .0001[b]	.08	422,176.06	.06	.02	.12
	Model 3: occ + sex + age + educ + dom	58.35 (277, 58627)	< .0001	.22	412,694.39	.06	.01	.12
	Model 4a: occ + sex + age + educ + dom + income	60.21 (278, 54401)	< .0001	.23	381,210.71	.05	.01	.11
	Model 4b: occ + sex + age + educ + nuances	59.97 (298, 58577)	< .0001	.23	411,189.23	.06	.05	.06

Note. [a]Pre-registered variables: occ = occupation, educ = education, dom = Big Five personality domains; [b]Statistically significant after Holm-Bonferroni correction; [c]Effect sizes and 95% confidence intervals for 4-digit ISCO occupational group.

Table 5 features the occupations with the highest and lowest smoothed mean JS scores, where the difference between the top and the bottom occupation's JS was about 11 T-scores (1.1 SDs), and the top and bottom 10 differed over 9 T-scores. Among the occupations reporting the highest levels of JS were several healthcare-related professions, such as dentists, midwifery professionals, physiotherapy technicians and others, but also software developers, authors and religious professionals. Conversely, the lowest JS appeared among more elementary type of jobs, including transport, storage and manufacturing laborers, kitchen helpers, cleaners and stock clerks. Also, waiters and various types of sales workers were among those with the lowest JS.

Table 4

Occupations With the Highest and Lowest Smoothed Mean Life Satisfaction Scores, Adjusted for Age, Sex, Education, and Personality Domains

Ranking	Occupation	Count	LS
Highest	Religious Professionals	29	54.32
	Sheet Metal Workers	34	53.73
	Self-employed/Sole Proprietors	69	53.60
	Medical Assistants	73	53.52
	Psychologists	245	53.49
	Health Professionals Not Elsewhere Classified	59	53.20
	Specialist Medical Practitioners	345	52.69
	Special Needs Teachers	186	52.65
	Physiotherapy Technicians and Assistants (Massagists)	155	52.59
	Mixed Crop and Animal Producers	197	52.59
Lowest	Security Guards	164	47.00
	Mail Carriers and Sorting Clerks	135	47.06
	Survey and Market Research Interviewers	26	47.26
	Driving Instructors	42	47.30
	Waiters	216	47.36
	Contact Centre Salespersons	53	47.41
	Carpenters and Joiners	79	47.49
	Unspecified Heads of Shifts	167	47.55
	Chemical Engineers	36	47.61
	Butchers	40	47.66

Note. LS = life satisfaction.

Table 5

Occupations With the Highest and Lowest Smoothed Mean Job Satisfaction Scores, Adjusted for Age, Sex, Education, and Personality Domains

Ranking	Occupation	Count	JS
Highest	Dentists	222	55.38
	Midwifery Professionals	131	55.32
	Hairdressers	317	55.21
	Health Professionals Not Elsewhere Classified	59	55.13
	Authors and Related Writers	41	55.08
	Physiotherapy Technicians and Assistants (Massagists)	155	54.94
	Software Developers	877	54.49
	Religious Professionals	29	54.48
	Medical Imaging and Therapeutic Equipment Technicians	77	54.25
	Beauticians and Related Workers	371	54.22
Lowest	Transport and Storage Labourers	64	44.58
	Manufacturing Labourers	502	44.60
	Kitchen Helpers	72	44.64
	Sales Workers Not Elsewhere Classified	316	45.13
	Elementary Occupations	164	45.35
	Waiters	216	45.53
	Contact Centre Salespersons	53	45.63
	Product Graders and Testers (excluding Foods and Beverages)	78	45.93
	Domestic, Hotel and Office Cleaners and Helpers	530	45.96
	Survey and Market Research Interviewers	387	46.06

Note. JS = job satisfaction.

Mean LS and JS scores for all occupations, adjusted and unadjusted, smoothed and not, are in the online supplementary material (available here: https://osf.io/sqj3c/files/osfstorage?view_only=bc6649e31254419da5a747007794129d).

Exploratory analyses

Could income account for the associations?

The addition of personal income to the model had a small impact on explaining satisfaction. For JS the R^2 increased slightly, suggesting income explained some additional variance. For LS, the R^2 was unaffected, indicating that income did not have any significant additional explanatory power. The effect of occupation (η^2) decreased slightly in both models, suggesting that some of the occupational differences in satisfaction were attributable to variation in income. Overall, income contributed to satisfaction, but its effect was modest, explaining 0.5% of the variance in LS and 2.5% in JS (for details, see Table 3 and Supplementary Table 1).

Could personality nuances account for the associations?

We also addressed LS's, JS's and occupations' nuanced associations with personality traits by substituting the Big Five domains with the 21 personality nuances varying the most (and generally more than the Big Five domains) among occupations (Anni et al., 2024). The model fit improved for LS compared to using the Big Five personality domains with considerable differences in R^2 (change from .46 to .54) but only marginally for JS (R^2 change from .22 to .23; see Table 3 and Supplementary Material Table 1 for detailed results). The effect of occupation (η^2) decreased slightly (from .02 to .01) after replacing the Big Five domains with the personality nuances in the LS model. So, nuances explained more occupational differences in LS but did not fully account for them. The effect of occupation remained the same ($\eta^2 = .06$) in the JS models, indicating that nuanced personality differences did not further explain occupational differences in JS.

Characteristics of jobs with more and less satisfied incumbents

Next, we explored whether job prestige and job-typical Work Values and Interests, as characterized by O*NET, were associated with LS and JS to better understand what, specifically, about occupations may contribute to satisfaction levels. Table 6 shows the Spearman correlations between job characteristics and occupations' smoothed mean LS and JS scores after controlling for the mean personality traits of each occupation (derived from Anni et al., 2024), besides age and gender.

Overall, job characteristics were more strongly related to JS than LS, which is expected given that variables such as achievement and working conditions likely have a more direct influence on how people feel about their jobs rather than their overall LS. Among O*NET Work Values, Achievement showed a significant positive correlation with JS ($r = .19$, $p < .05$), suggesting that occupations offering greater opportunities to accomplish meaningful goals are more satisfying, even after adjusting for the personality traits of the people holding these jobs (likely due to job-selection effects). However, other Work Values were not significantly associated with either LS or JS after controlling for occupational mean personality.

Table 6

Partial Correlations between Satisfaction Scores and O*NET Values and Interests Controlling for Mean Occupational Big Five Personality Traits

Variable	Life Satisfaction	Job Satisfaction
SIOPS score	.01	.12
O*NET Values		
Achievement	.09	.19*
Working Conditions	.04	.08
Recognition	.04	.14
Relationships	.02	.11
Support	.03	.09
Independence	.05	.11
O*NET Interests		
Investigative	.01	.17*
Artistic	.03	.12
Realistic	.24***	.27***
Enterprising	-.25***	-.27***
Social	-.03	.09
Conventional	-.21**	-.29***

Note. SIOPS = Standard International Occupational Prestige Scale. $k = 263$ occupational groups for correlations with SIOPS prestige score and $k = 213$ for all other correlations. All p-values are adjusted with Benjamini-Hochberg method; *** $p < .001$, ** $p < .01$, * $p < .05$.

Stronger associations emerged among the O*NET Interests. Job-holders realistic interest levels were positively associated with both LS ($r = .24$, $p < .001$) and JS ($r = .27$, $p < .001$), whereas enterprising interests were negatively associated with both ($r = -.25$, $p < .001$ for LS; $r = -.27$, $p < .001$ for JS). Conventional interests also showed a significant negative correlation with both LS ($r = -.21$, $p < .01$) and JS ($r = -.29$, $p < .001$). Investigative interests were positively related to JS ($r = .17$, $p < .05$), though not to LS. These findings suggest that occupations with the higher realistic orientation scores tend to be with higher mean satisfaction, while occupations with higher enterprising and conventional orientation tend to be linked to lower satisfaction.

Notably, job prestige (SIOPS score) was not significantly associated with LS or JS after controlling for occupational personality traits. These findings indicate that the nature of the work itself—especially certain interest inclinations—may play a more important role in satisfaction than job prestige, once personality traits are accounted for. This indicate that the prestigious jobs are not by default more satisfying.

Discussion

Our results, based on a large population sample spanning 263 occupations with comprehensive psychological assessment, suggest that jobs explain a significant proportion of variance in LS and JS. This applied even after we accounted for age, education, and personality traits that may have led to people self-select to the occupations and confound occupational differences in satisfaction. For reference, occupational differences in LS were comparable or bigger than the effects of major life events and transitions (Bühler et al., 2023). For instance, marriage, divorce and childbirth explained less than 0.5% of the variance in LS change (Bühler et al., 2023), whereas occupations accounted for 1-5% of LS variability and up to 7% of the variability in JS. Moreover, while the effects of events and transitions may wane due to habituation (Anvari et al., 2023), the effects of occupational differences in LS and JS could persist or even cumulate over time (Funder & Ozer, 2019), given the regular exposure to occupational circumstances in everyday life. Specifically, while many occupations are relatively average in their satisfaction levels and hence their differences smaller, the differences are considerable when comparing occupations at opposing tail ends of our ranking of 263 occupations. So, although personality traits remain the primary predictors of LS and JS, our results suggest that occupational role may be among the most important contextual factors above and beyond personality traits, especially for JS but also for LS.

The importance of a fine-grained job classification

With data about 263 occupations, we had the unique opportunity to observe differences between occupations beyond broad categories studied previously (see Table 1 for overview). We found that high as well as low LS and JS were reported both by white and blue-collar workers (see Tables 4 and 5). For example, after accounting for personality traits, butchers as well as contact centre salespersons seem to have similarly low LS. At the same time, religious professionals and metal workers both reported to enjoy high LS. Likewise, low JS was observed among kitchen helpers as well as market research interviewers, whereas high JS was reported by dentists and writers, as well as hairdressers and beauticians. These findings add important detail to existing studies that have used broad occupational categories that are likely to obscure job role or industrial sector variances within the categories (e.g., Easterlin et al., 2011; Georgellis et al., 2022; Hessels et al., 2018; Hofmann et al., 2018; Ravina-Ripoll et al., 2021; Seiler Zimmermann & Wanzenried, 2019).

The most and least satisfying jobs

In terms of LS, religious professionals, sheet metal workers, and self-employed (sole proprietors) were among those reporting the highest scores. Several health-related occupations also appeared in the top LS group, including medical assistants, psychologists, and specialist medical practitioners. Notably, sheet metal workers and mixed crop and animal producers represent more manual and traditionally blue-collar jobs that nonetheless rank highly in LS, highlighting that high satisfaction is not exclusive to highly educated or white-collar professions.

At the lower end of the LS spectrum, occupations such as security guards, mail carriers, and survey and market research interviewers reported the lowest levels of LS. Other low-ranking roles included contact centre salespersons, waiters, and butchers, suggesting a group of jobs characterized by routine or some physical demands.

The highest mean JS scores were reported by dentists, midwifery professionals, and hairdressers. These were followed by health professionals not elsewhere classified (primarily creative therapists) and authors, indicating that occupations involving relatively more hands-on care work, as well as creative professions, can be particularly rewarding.

At the opposite end, several more elementary occupations (transport, storage and manufacturing labourers, and kitchen helpers) showed the lowest JS levels. Other occupations with low JS included waiters, contact centre salespersons, and survey and market research interviewers—all of which appearing in both low LS and low JS categories.

These findings illustrate that satisfaction at work and in life can vary substantially between occupations, and that both high and low satisfaction can be found across different sectors and skill levels.

What could explain occupational differences in satisfaction?

Covering over 250 diverse occupations, we could systematically investigate job-related factors characterizing occupations with different satisfaction levels. First, consistent with previous studies (Navarro & Salverda, 2019; Ng & Diener, 2014; Ngamaba et al., 2020;

Tan et al., 2020), we found that occupations with higher typical income tended to be associated with slightly higher satisfaction. Even after controlling for occupation, sex, age, education, and personality traits, income remained a small but statistically significant predictor of both LS and JS. The effect sizes were rather modest, with $\eta^2 = .005$ for LS (approximately $r = .07$) and $\eta^2 = .025$ for JS (approximately $r = .16$).

Second, although previous studies have reported positive associations between occupational prestige and satisfaction (e.g., Andrade et al., 2019; Hofmann et al., 2018; Ng & Diener, 2014; Ngamaba et al., 2020), we did not observe a clear relationship in the present study after accounting for occupational personality traits. The SIOPS prestige scores were not statistically significantly associated with either LS ($r = .01$) or JS ($r = .12$), although the positive association with JS may hint to potential trend worth exploring further with higher number of occupational groups. This suggests that more prestigious jobs are not that necessarily more satisfying, once differences in the personality profiles typical of those occupations—and hence, possible self-selection-into-jobs effects—are accounted for.

We also explored two kinds of job-level characteristics derived from the O*NET database, Values and Interests. Among the Work Values, only Achievement showed a significant positive correlation with JS ($r = .19$, $p < .05$), indicating that occupations affording opportunities to accomplish meaningful goals tend to have more job-satisfied incumbents, net of personality trait differences among the jobs. Other values were not significantly related to LS, although the associations showed some positive trends with JS, suggesting that aspects like Recognition ($r = .14$), Relationships, and Independence (both $r = .11$) may play a modest role in how people experience their work.

More associations emerged for the O*NET Interests. People on jobs characterised with Realistic interests, which reflect practical, hands-on activities, tended to have higher LS ($r = .24$, $p < .001$) and JS ($r = .27$, $p < .001$). In contrast, Conventional interests, associated with structure and rule-based tasks, were negatively associated with LS ($r = –.21$, $p < .01$) and JS ($r = –.29$, $p < .001$). Enterprising interests, which involve persuasion, leadership and competitiveness, also showed negative associations with LS and JS ($r = –.25$ and $–.27$, respectively). However, despite the negative associations with Enterprising interests, self-employed individuals—many of whom likely engage in enterprising roles—were among those reporting the highest LS, consistent with previous studies highlighting the well-being benefits of self-employment (Hessels et al., 2018; Ravina-Ripoll et al., 2021; Stephan et al., 2023).

Additionally, Investigative interests were positively related to JS (r = .17, p < .05), suggesting that occupations involving analytical thinking, problem-solving, and research can be particularly fulfilling. In our data, this association was probably largely driven by occupations in the medical field, such as general and specialist medical practitioners, dentists, medical assistants and others, which score high on Investigative interests and tended to report higher JS. Artistic and Social interests showed no significant associations with either LS or JS, possibly due to varying work conditions and demands in these roles.

Taken together, these findings suggest that income may matter more than prestige for LS, and that specific job characteristics—particularly the interests involved in the jobs—are meaningfully linked to how satisfying incumbents are, even after adjusting for occupation-typical personality traits. So, income and job nature may matter more than status.

Implications

Our results have implications for both researchers and practitioners. For well-being researchers, the findings contribute to the ongoing challenge of identifying specific, impactful factors that shape people's overall satisfaction—a task that has proven difficult, as many commonly assumed influences tend to have modest or inconsistent effects (Bühler et al., 2023; Luhmann et al., 2012). Our results suggest that occupation is one such meaningful factor. It is a particularly relevant domain in this context, as it often entails long-term exposure to specific environments, demands, and roles that may shape well-being trajectories over time.

Also, the results highlight the need to consider personality traits when seeking to explain variances in LS or domain satisfactions such as JS. On one hand, they may impact LS and JS directly (Diener et al., 1999); on the other, they influence occupational choices, as individuals self-select or are selected into roles and industries that align with their personality profiles (Anni et al., 2024). Yet, the inclusion of personality traits in studies investigating the links between occupational categories and LS as well as JS is still relatively rare. We demonstrated that accounting for the role of personality traits in the variance of LS and JS, they vary less with jobs. This is consistent with previous findings based on a smaller sample (Törnroos et al., 2019).

Furthermore, the observed correlations between O*NET scores and satisfaction outcomes offer insights into the kinds of occupational characteristics that are linked to lower or higher satisfaction. Our findings suggest that less prestigious jobs could be equally fulfilling than more prestigious ones, particularly when they offer adequate income, tangible tasks, and a clear sense of progress. Jobs associated with high Realistic interests—such as those involving practical, hands-on work or technical problem-solving—may support satisfaction by offering concrete outcomes, low ambiguity, and opportunities for skill-based mastery. In contrast, leadership roles (high in Enterprising interests) and highly structured, rule-bound occupations (high in Conventional interests) may be linked to lower satisfaction, potentially due to increased possibly of increased stress, pressure or responsibility. Whether such dissatisfaction is an unavoidable feature of certain occupations or something that can be mitigated through better job design (Bakker & Demerouti, 2017) remains to be studied further. Understanding these associations more thoroughly could help improve not only workplace well-being but also performance, commitment, and retention (Searle & Auton, 2015).

For practice, particularly in vocational and occupational counselling, our findings point to the value of considering both personality traits and occupational characteristics when supporting individuals. This approach can improve career guidance and inform satisfaction-focused interventions, helping people find roles that better align with their preferences and strengths.

Strengths and limitations

This study offers several methodological and conceptual advances over previous research on occupational differences in LS and JS. Using a large, population-based sample, we examined satisfaction across 263 specific occupations—far beyond the broad groupings used in earlier studies—revealing more detailed rankings. We also controlled for individual personality traits, ensuring that observed occupational differences reflect job-related context rather than self-selection based on disposition. These strengths enhance the study's theoretical insights into workplace well-being and its practical relevance for career guidance and policy.

It is worth noting that these results were found on a single dataset albeit a large one. It is therefore difficult to predict the extent to which they are generalisable to the entire population of Estonia let alone other countries as well as cultural contexts. Still, the 95% confidence intervals of the partial η^2s in our main models were small, indicating a low degree of uncertainty about the true effect size in this particular population. Moreover, there may be specific antecedents of LS and JS that we could not account for in our models, most notably job-related stressors and the specific means by which our respondents could have been able (not) to mitigate them. Therefore, there is a proportion of LS and JS that is left unexplained.

Conclusion

Overall, the results indicate that occupational role significantly contributes to the variance in both LS and JS. In fact, with effect sizes comparable to or even exceeding those of major life events and circumstances—such as health problems, unemployment, or marriage—occupational role may be one of the most important influences on satisfaction and well-being. As such, the data provide an important starting point for further enquiries about the occupational factors the predict high or low LS and JS. We highlighted the need to account for differences in personality traits given people self-select into industries as well as job roles. A more detailed understanding of what job characteristics contribute to life and JS will help design better job roles and support organisations to cultivate higher satisfaction of their employees.

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