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Job characteristics and personality change in young adulthood: A 12-year longitudinal study and replication

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Abstract

Objective: Personality changes are related to successfully performing adult occupational roles which require teamwork, duty, and managing stress. However, it is unclear how personality development relates to specific job characteristics that vary across occupations.

Method: We investigated whether 151 objective job characteristics, derived from the Occupational Information Network (O*NET), were associated with personality levels and changes in a 12-year longitudinal sample followed over the school to work transition. Using cross-validated regularized modeling, we combined two Icelandic longitudinal datasets (total $N = 1054$) and constructed an individual-level, aggregated job characteristics score that maximized prediction of personality levels at baseline and change over time.

Results: The strongest association was found for level of openness (0.25), followed by conscientiousness (0.16) and extraversion (0.14). Overall, aggregated job characteristics had a stronger prediction for personality intercepts (0.14) than slopes (0.10). These results were subsequently replicated in a U.S. sample using levels of the Big Five as the dependent variable. This indicates that associations between job characteristics and personality are generalizable across life stages and nations.

Conclusions: Our findings suggest that job titles are a valuable resource that can be linked to personality to better understand factors that influence psychological development. Further work is needed to document the prospective validity of job characteristics across a wider range of occupations and age.

KEYWORDS

job characteristics, longitudinal, O*NET, personality change, young adulthood

1 | INTRODUCTION

Occupations form central aspects of the sense of self (Phelan & Kinsella, 2009), explaining the ubiquitous conversation starter: "So, what do you do?" Many people perform job tasks for approximately half of their waking hours, and in certain high stress jobs, work consumes even more time and energy (Khubchandani & Price, 2020). A significant body of research has examined the interface between work and personality (i.e., patterns of thinking, feeling, and behaving that are relatively stable across time and context). Personality trait differences are associated with job performance (Barrick et al., 2001), coping with work-related stress (Wu, 2016), motivation to pursue different styles of work (Bipp, 2010), and career path decisions (Lounsbury et al., 2003). Similarly, occupational experiences may guide the development of adult personality (e.g., Holman & Hughes, 2021; Stahlhofen et al., 2022; Wille & De Fruyt, 2014; Woods et al., 2019; Wu, 2016). Indeed, starting work (Specht et al., 2011), stopping work (Schwaba & Bleidorn, 2019), choosing between work-related roles (Golle et al., 2019), and regional norms concerning the normative timing of initiating work (Bleidorn et al., 2013) have been linked to shifts in personality development.

However, previous studies linking work and personality have produced inconsistent findings in terms of the magnitude and, in some cases, the direction of effects (Bleidorn et al., 2018). One potential explanation for these inconsistencies is that most previous studies have linked limited sets of job characteristics or general work transitions (e.g., starting work) to personality development (Golle et al., 2019; Jackson et al., 2012). Here, we use a predictive[1] modeling framework applied to a combined 12-year longitudinal study to evaluate the extent to which a holistic set of job characteristics were associated with personality levels and change across time. Each longitudinal sample was well-powered and had at least three measurement waves for personality change estimates. Our primary goal was to demonstrate the benefits of an atheoretical comparison across a common set of job characteristics available to all researchers, inspired by calls for longitudinal, experience-wide association studies (Bleidorn et al., 2020). We also examined the utility of aggregating individual job characteristics into a single index (i.e., a polyO*NET index) in predicting personality level and change, which combines the joint predictive power of over hundred effects. Results reveal the extent to which job titles are associated with personality development with implications for understanding how work structures and shapes people's lives.

1.1 | Personality development and occupational experiences

People tend to become more conscientiousness, agreeable, and emotional stable across development (Bleidorn et al., 2022; Roberts et al., 2006). From a macro-perspective, such changes can be partially explained by the social investment principle (Roberts & Wood, 2006), which posits that certain social roles, such as being an employee, are expected to promote and reinforce behavioral norms and expectations that facilitate more socially mature personality traits (i.e., increases in conscientiousness, agreeableness, and decreases in neuroticism). For example, Roberts et al. (2003) found that financial security and occupational prestige were associated with reductions in negative emotionality, and achievement-oriented personality increased in jobs with the ability to hire and fire employees. Similarly, Hudson et al. (2012) found that identification and investment with work were associated with personality change; individuals who invested in work more also tended to increase in conscientiousness. At a broader level, individuals living in nations where it is more typical to begin work at earlier ages tend to show earlier increasing age-trends in emotional stability and conscientiousness (Bleidorn et al., 2013). It may be the case that cultural norms surrounding work and gaining adult occupational roles, rather than remaining with family or continuing education, also guide personality development.

Labor sectors and organizations also tend to contain employees with specific personality dimensions through processes of attraction, selection, and attrition (Schneider, 1987). For instance, highly introverted individuals may be attracted to jobs such as mail carriers with little social interaction, and individuals high on agreeableness are more likely to leave jobs that require giving criticisms and argumentation. Once in a job, occupational experiences may shape personality development due to transactions between work demands and personal characteristics that inform values, motivation, and goals (Nye et al., 2012; Woods et al., 2019). For example, Wille and De Fruyt (2014) found that individuals with lower openness tended to work in more conventional environments, which was associated with accelerated decreases in openness 15 years later. Broadly, these findings can be interpreted with the corresponsive principle of personality development (Roberts et al., 2003), which proposes that people often choose work environments that align with their personality, interests, and skills, and these environments then provide opportunities to develop and enhance these attributes (Li et al., 2014). In other words, the experiences one has at work (e.g., bonding with a coworker or receiving a reprimand from a boss) may trigger momentary person-work transactions, and when repeated, these experiences may be associated with state variation and short-term trait regulation, which could ultimately transform into long-term trait changes (e.g., TESSERA framework of personality change; Triggering situations, Expectancy, States/State expressions, and Reactions; Wrzus & Roberts, 2017).

Woods et al. (2019) integrated several relevant theoretical models and concepts in the Demands-Affordances TrAnsactional (DATA) model. The DATA model explains that work environments demand products and behaviors while also providing opportunities for social feedback from peers (i.e., coworkers) or authority figures (i.e., bosses). Ideally, when an employee's job demands are accurately calibrated to their abilities, and the job will provide adequate affordances for job satisfaction. Given that job demands may be difficult to change (without attrition), personality may develop in a direction to match the demands and affordances of the work context (Su et al., 2015; Woods et al., 2019). For example, workers facing challenging situations and role expectations may lead to change in openness, such that tackling a tough challenge with an innovative idea may lead to increases in openness (e.g., Nieß & Zacher, 2015). The DATA model proposes that trait change is the consequence of accumulated micro-transactions with the work environment, suggesting that recurrent work characteristics, such as the activities and environment of work, guide personality development.

A study in this Special issue (Stahlhofen et al., 2022) found associations between job characteristics and personality traits. For example, a more innovative work environment was associated with higher levels of extraversion and lower levels of neuroticism, while less manual labor was associated higher levels of openness. Higher levels of social integration were associated with higher levels of conscientiousness, agreeableness, and emotional stability. However, despite many associations between occupational experiences and personality at baseline, personality *change* across 20 years was weakly correlated with work characteristics, except for a less pronounced decrease in neuroticism in more innovative environments. This result may be due to the timing of assessments, both in terms of the length of time between assessments (i.e., 20 years) and when in an employee's career the assessments are taken (i.e., during middle adulthood, when the career phase and personality traits are more stabilized). It may also be the case that subjective ratings of the work environment may be less comprehensive, subject to reporting bias, or miss important factors due to lack of experience with different sorts of jobs (see Rauthmann et al., 2015 for discussion on unique contribution of objective stimulus on psychological phenomenon).

In summary, prior research indicates that certain job characteristics are associated with personality development. However, most associations are modest, and few replicable associations have been found. It may be the case that a large number of small effects linking job characteristics and personality change may aggregate across the life span, highlighting the potential utility of considering a broader range of job characteristics that relate to personality levels and changes. To date, most studies have focused on one or two work demand(s) and constructed theoretical frameworks tailored to those demands. This pattern is also common in empirical research on personality development and life events. Denissen et al. (2019) is exceptional in this respect, having included eight life events structured around adult social role transitions and loss events. Yet, these major and rare life events (e.g., unemployment) were weakly associated with personality development. Many more life events likely contribute to personality development, some of which reflect quotidian aspects of life (e.g., a difficult experience with a boss; making a sale) that are not easily assessed (Tucker-Drob & Briley, 2019).

1.2 | Longitudinal experience-wide association study

Examining a broader range of job characteristics is crucial to better understand how work affects personality development (Woods et al., 2019). Bleidorn et al. (2020) proposed reorienting personality development research toward longitudinal experience-wide association studies. These authors argued that the field of behavior genetics experienced a similar research trajectory and was relatively successful in shifting research practices to build more replicable, cumulative evidence. Early candidate gene studies attempted to link a specific genetic polymorphism with an outcome using well-reasoned theory and typical sample sizes (e.g., $N = 100$); however, essentially none of the reasonable and theoretically justified hypotheses withstood empirical scrutiny (Border et al., 2019). Instead, links between genetic variants and many outcomes have been documented using genome-wide association studies (Visscher et al., 2017). This methodological advance required very large sample sizes, international collaboration with expectations for data sharing, and a map of the human genome (see supplement for additional methodological information). Innovative statistical methods (e.g., polygenic risk scores; Dudbridge, 2013) were created to aggregate millions of tiny associations into a composite. This approach of aggregating the effects of numerous small associations to produce an individual-level score has also been applied in fields beyond behavior genetics. For example, Mõttus and Rozgonjuk (2021) used personality items rather than genetic variants to create an aggregated score (i.e., weighted sum of all items with the weights representing the strength of association) that predicted over 40% of the variance in chronological age.

In our view, the field of personality development will accelerate most quickly through methods that obtain a wide range of information about an individual's experiences using limited data. Job titles meet this criterion, as they provide rich information concerning characteristics that reflect everyday affordances that can constrain or allow for personality-related behaviors (e.g., objective aspects of the work environment, or activities; Rauthmann et al., 2015). Additionally, occupations are well-documented and categorized, providing valuable information for individuals seeking to understand the requirements and characteristics of different jobs. For example, the Occupational

Information Network (O*NET; www.onetonline.org) provides expert-rated job characteristics covering a range of information, including the necessary skills and knowledge for a job, interests, typical work activities, and work context (e.g., typically indoors vs. outdoors). O*NET complements previous studies which focused on subjective job ratings by providing a more objective assessment of typical occupational experiences, environments, and demand (Sonnega et al., 2018). In addition, studying a wider range of job characteristics may reveal associations between job characteristics and changes in multiple personality traits. The demands of a particular job can restrict or facilitate behaviors related to various personality traits, potentially leading to correlated changes in an individual's personality (Allemand & Martin, 2016). Thus, a single question asking a participant their current job title can provide unique information concerning recurrent behaviors and contextual demands.

1.3 | Current study

Building on the call for longitudinal experience-wide association studies, we apply data analytic techniques from behavior genetics to personality development using a common set of job-related variables available to all researchers. As research regarding a broad range of job characteristics and personality development need more investigation, we use a predictive modeling framework (Yarkoni & Westfall, 2017) to evaluate the extent to which personality levels and change were associated with a large set of job characteristics derived from a single item: one's job title. We also focus primarily on aggregating small effect sizes into a composite (i.e., polyO*NET score), rather than identifying specific in predicting personality trajectories. By linking job titles with the rich and open access data from O*NET, we demonstrate a typical set of analyses that can be performed under a longitudinal experience-wide association study approach. We had three primary research questions:

1. *To what extent are objective, individual job characteristics associated with personality levels or change?* To address this research question, we calculated the association between each job characteristic and personality level and changes.
2. *To what extent can a single polyO*NET predict personality level or change?* To address this research question, we constructed an algorithm to aggregate personality-relevant job information across all job characteristics and then we tested the extent to which this aggregate score was associated with personality levels and changes.
3. *To what extent do the job characteristics that are predictive of one personality domain overlap with other domains?* To address this research question, we correlated the aggregated job characteristic scores (i.e., polyO*NET index) across domains (i.e., the big five) and developmental features (i.e., levels and changes).

Our goal is to take advantage of the rich data from the O*NET to identify associations between job characteristics and personality development. Identifying individual job characteristics linked to personality development can inform theoretical models of the type of environmental demands to which each personality dimension responds. The correlation between the polyO*NET index and personality gives some indication of the aggregate strength of association between job characteristics and personality development. Additionally, associations among polyO*NET indices may suggest the extent to which job characteristics induce correlated change in personality (Olaru & Allemand, 2022). If these associations are meaningful and generalizable, then the polyO*NET index can be useful for a wide range of future studies assessing personality change in adulthood.

2 | METHOD

2.1 | Participants and procedure

Participants were drawn from two longitudinal samples ($N_1 = 485$, 47% female; $N_2 = 1338$, 50% female) collected in Iceland that include measures of personality across multiple waves from late adolescence (~age 15–18) to young adulthood (~age 27–30).[2] Effective sample size (i.e., participants who reported a job title) is $N_1 = 323$ and $N_2 = 731$, respectively. Both samples of Icelandic youth were representative of the total student population based on gender, educational tracks, and residential location (Einarsdóttir & Rounds, 2007). The survey data for Sample 1 and 2 were first collected in 2006 as part of the standardization of the Icelandic Interest Inventory (Einarsdóttir & Rounds, 2007). Participants were enrolled during their final year of compulsory education (Sample 1) and in upper-secondary education (Sample 2), and they were contacted via emails and phone calls (for non-responders) during follow-up waves.

The samples differed in two primary ways. First, Sample 1 included five waves of measurement (ages 15.3, 17.7, 21.7, 23.7, 26.7 years, on average), whereas Sample 2 included three waves (ages 17.6, 20.6, and 23.6 years, on average). Second, Sample 1 participants were slightly younger at study onset (M age = 15.3 years old) than those in Sample 2 (M age = 17.6 years old).

For our main analyses, we combined these samples and used a permutation approach (i.e., rerunning the model on many randomly selected training and testing subsets) to average over any differences (see analytic approach for more details). More detailed information regarding the sampling procedure can be found on page 3 of supplementary materials.

2.2 | Attrition

We included participants with a current job title (i.e., available job characteristic profiles), resulting in a final sample of 1054 ($N_1=323$, $N_2=731$). Sample descriptions can be found in Table S1–S5, and zero-order correlations among all variables can be found in Table S2. In both samples, attrition analyses found significant correlations between having a current job and being a male ($r=0.19$, 95% CI = [0.11, 0.28]), and being more agreeable at the first wave (Sample 1: $r=0.12$, 95% CI = [0.06, 0.17]; Sample 2: $r=0.12$, 95% CI = [0.03, 0.21]). Additionally, participants who provided more waves of data tended to be female (Sample 1: $r=-0.16$, 95% CI = [−0.25, −0.08]; Sample 2: $r=-0.13$, 95% CI = [−0.18, −0.07]). Finally, Sample 2 participants who dropped out scored lower on agreeableness ($r=-0.12$, 95% CI = [−0.17, −0.06]) and openness ($r=-0.08$, 95% CI = [−0.13, −0.02]) at the initial wave.

2.3 | Temporal order of measures

During the studies, personality measures were included at each wave. Since some participants only entered workforce at a later wave (i.e., job titles were collected at a more recent wave), their personality trajectory was captured prior to employment. The average gap between the time when personality measures were first collected and the time when participants reported their job titles was 5.02 years apart. As the personality assessments were largely, but not entirely, prior to employment, we conducted an exploratory analysis on the subset of participants ($N=226$ vs. $N=1054$ for main analyses), who reported job titles midway and had at least two subsequent waves of personality measures following up employment. Given the constraint on number of subsequent measurement waves, all subset participants were part of Sample 1 (i.e., included maximum of five waves vs. three waves). Sensitivity analyses did not reveal significant differences between participants who reported employment earlier versus those who entered the workforce later, ranging from age ($r=-0.02$, 95% CI = [−0.13, 0.08]) to openness ($r=-.10$, 95% CI = [−0.21, 0.01]).

2.4 | Measures

2.4.1 | Personality

Across both datasets, participants provided self-report ratings of their Big Five personality at each wave, using the Icelandic version of the NEO-FFI (Jónsson & Bergþórsson, 2004). The measure contains 60 total items, 12 for each Big Five trait (i.e., neuroticism, extraversion, openness, agreeableness, and conscientiousness). In both samples, all personality traits were fully or partly consistent with scalar invariance across time (Hoff et al., 2021). Alpha reliability ranged from 0.67–0.85 (see Table S1–S5 for domain-specific alphas per trait at wave 1).

2.4.2 | Job characteristics

We used the Occupational Information Network (O*NET; https://www.onetonline.org/) to derive standardized job characteristics for each participant's job. O*NET, an extensive database containing job analysis data on 923 occupations, is developed and maintained by the U.S. Department of Labor (Pellegrino & Hilton, 2012; Peterson et al., 1999). O*NET uses a combination of expert ratings and job incumbent surveys to measure job characteristics. Samples of job incumbents were selected from representative businesses to provide ratings for occupation-related knowledge, work activities, work context, educational and training requirements (job zones), and work styles. This process involved surveying employees with questions, such as, "did the job require communicating with people outside the organization?" Ratings on interests, skills, values, and abilities were provided by trained raters by considering each occupation's title and description, core tasks, knowledge, and generalized work activities. Interrater reliabilities for job descriptions were acceptable, with most competencies reaching 0.7 with an average of 10 raters (Peterson et al., 1999).

We linked 247 O*NET variables to our dataset by matching participants' most recent job titles to O*NET job titles (see Hanna et al., 2021 for additional details). Briefly, trained research assistants translated participant-reported job titles from Icelandic and matched the title with an O*NET category. Agreement across raters was high (~80%). Discrepancies were resolved by three experts. The 247 O*NET variables come from one of nine categories:

Ability. Abilities refer to one's capability to perform 52 specific tasks. Ratings range from 1 (not important) to 5 (extremely important). For example, the job "air traffic controller" has a high importance rating for the ability *problem sensitivity*, and actor has a high importance rating for *oral expression*.

Interest. Occupational interest profiles (Rounds et al., 2013) describe jobs according to Holland's (1997) RIASEC (Realistic, Investigative, Artistic, Social, Enterprising, and Conventional) types. The interest profiles reflect the extent to which each occupation exemplifies each of the six types, ranging from 1 (does not exemplify the interest) to 7 (perfectly exemplifies the interest). For example, childcare worker has a score of 7 for *social interest*.

Job Zone. Occupations were categorized into one of five job zones to capture each occupation's complexity based on how much education, job-related experience, or on-the-job training is required. The job zone scores ranged from 1 (require little to no preparation, e.g., cleaner) to 5 (require extensive preparation, e.g., physician).

Knowledge. Knowledge refers to sets of facts and principles needed to perform a job well. O*NET included 33 knowledge areas, with ratings ranging from 1 (not important) to 5 (extremely important). For instance, *biology* is the highest rated knowledge category for an animal scientist, and the highest rated knowledge category for a head chef is food production.

Skill. Skills refer to 35 work-related behaviors that are considered critical for a wide range of jobs and tasks. Rating ranged from 1 (not important) to 5 (extremely important). *Active listening* is the highest rated skill for a lawyer.

Work Activity. Work activities included 41 commonly performed activities with rating range from 1 (not important) to 5 (extremely important). *Working with a computer* is the highest rated activity for a programmer.

Work Context. Work context included 57 possible work settings, including potential job-related hazards, pacing of work, and interpersonal factors. Frequency of the contexts were rated as 1 (never) to 5 (every day). An example job that requires *frequent standing* is restaurant cook.

Work Styles. Work styles refer to typical personal characteristics of employees in each occupation, originally developed by examining existing taxonomies of personality (Kyllonen et al., 2014). We included 16 styles, which ranged from 1 (not important) to 5 (extremely important). An example job rated highly on the work style of *dependability* is registered nurse.

Work Values. Work values refer to 6 global aspects of work (i.e., achievement, independence, recognition, relationships, support, and working conditions) that are important to employees' satisfaction in each occupation, ranging from 1 to 7. *Achievement* is the highest rated value for competitive athletes.

Initial inspection of the O*NET job characteristics prior to linking with participant data indicated substantial redundancies in some job characteristics. For example, jobs requiring high levels of stamina would also require high levels of dynamic strength and static strength ($r = 0.93$). Extreme collinearity can result in unstable or difficult to interpret results. To minimize redundancy, we selected proxy job characteristics in the O*NET data to represent groups of highly correlated variables, with a cut-off value of $|0.8|$ for high correlations. Among each cluster of highly correlated variables, we identified the job characteristic that could best serve as a proxy (i.e., highest average absolute correlation with other job characteristics). This approach ensures that extreme collinearity and variable redundancy does not substantially weaken the results, while also maintaining as full as possible content coverage. To filter out highly correlated variables, we first examined within-category correlations (e.g., correlating all O*NET abilities variables with each other). After removing highly correlated within-category variables, we then examined intercorrelations across all variables. We excluded 87 job characteristics through this process. After linking job characteristics to participant data, we performed a similar approach on the combined Icelandic dataset of Sample 1 and Sample 2. Based on jobs included in the sample, we further excluded 9 additional variables due to high collinearity. After this process, we included 151 job characteristics from 9 O*NET categories: abilities (22), interests (5), job zone (1), knowledge (27), skills (14), work activities (27), work contexts (40), work styles (12), and work values (3). For a more detailed description of the selected job characteristics, see Table S3.

2.5 | Analytical plan

The analytic plan for this study was preregistered on the Open Science Framework prior to conducting analyses[3] and analytic code and supplemental materials can be found on the project's page (https://osf.io/tqfh5/). We conducted all analyses in R (R Development Core Team, 2022) using the lavaan package (Rosseel, 2012) with full information maximum likelihood estimation to handle missing data (Enders & Bandalos, 2001) and the glmnet package (Friedman et al., 2010). Our presentation of results focuses on effect size estimation, rather than explanation or hypothesis testing. Analyses were conducted in four steps, corresponding to the four research questions.

2.5.1 | Personality growth

We first examined personality mean-level change using linear growth models (Bollen & Curran, 2006). We selected linear models over other alternatives (e.g., quadratic terms) because they best aligned with our research aim of examining the association between personality growth and job characteristics. Previous study using current Icelandic samples have established partial or fully scalar invariance of personality measures (Hoff et al., 2021). Each Big Five dimension was modeled as a function of time, with an estimated latent intercept and slope. The latent intercept represents the level of each trait at wave one; the latent slope represents the average rate of change in the dimension over two years. We fixed the loadings of the slope to equate the actual measurement time intervals (i.e., 0, 3, 6 for Sample 2), and freely estimated the residuals. We included sex (1 = male, 0 = female) as a covariate at the manifest variable level to control for potential sex differences. We saved intercept and slope factor scores from each sample and combined the datasets to use in subsequent analyses. The factor scores were then residualized for age and dataset (i.e., Sample 1 vs. Sample 2) effect.

2.5.2 | PolyO*NET index construction

Next, to estimate the extent to which job characteristics account for variance in personality growth, we constructed a polyO*NET index. This approach is similar to the polygenic index approach in molecular genetics (Dudbridge, 2013) and has also been used more recently as a polyphenotype approach in personality psychology (e.g., Arumäe et al., 2021; Mõttus & Rozgonjuk, 2021).

A polyO*NET index capturing the aggregated effect of job characteristics was constructed as a sum of job characteristics weighted by their empirical association with the outcome of interest (i.e., personality intercept and growth). We used cross-validated regularized regression (i.e., elastic net; Zou & Hastie, 2005) to calculate the weights. This approach effectively deals with multicollinearity and returns a parsimonious set of job characteristics by setting some predictors to zero. To prepare for regularized regression, the 151 job characteristics were normalized with a cut-off value |1| for high skewness. The online supplement provides a more detailed description of regularization and cross-validation approaches.

Predictive models were trained and validated in independent samples to guard against overfitting and provide robust evidence of predictive accuracy (Mõttus et al., 2020; Yarkoni & Westfall, 2017). We trained 10 models with the intercepts/slopes of the Big Five as dependent variables in 80% of the combined samples ($N = 843$) and validated in the 20% test sample. We regressed each intercept and slope factor on all 151 O*NET characteristics, and we repeated the procedure 100 times in random splits of the sample (100 permutations).[4] The correlation between the actual and expected intercept and slope factor scores for the Big Five in the validation dataset indicated the extent to which aggregated job characteristics were associated with personality. Figure 1 outlines the analytic approach and how we evaluated polyO*NET index performance.

2.5.3 | Job correlation

To evaluate the extent to which the job characteristics linked with one dimension were shared with other dimensions, we estimated correlations among all polyO*NET indices. Large, positive correlations would indicate that the job characteristics associated with one dimension tend to be shared with another dimension. Large, negative correlations would indicate that job characteristics associated with high levels of one dimension tend to be associated with lower levels of another dimension. Job characteristics capturing shared variance common across the traits could help account for personality co-development.

2.5.4 | Replication analyses

To examine the robustness of our findings, we replicated the polyO*NET prediction on personality levels using the Midlife in the United States study (MIDUS; Brim et al., 2004), a commonly used dataset for personality development studies (e.g., Olaru & Allemand, 2022). We used the first wave of MIDUS for this replication analyses to maximize sample size and minimize participants who transit into retirement. After removing participants without a job and accounting for non-independence within families by randomly selecting one of the sibling/twin pairs, the sample included 4505 participants. The abovementioned 151 job characteristics were linked via O*NET Standard Occupational Classification (SOC) codes to the 1980 Census Occupation Classification codes (OCC) used in MIDUS, following occupational-code crosswalk procedures suggested by LaPolice et al. (2008). When multiple O*NET-SOC occupations were linked to a single OCC code, the O*NET job characteristics were averaged. After cross-walking, the O*NET profiles included 499 (out of 923) combined/standalone occupations that matched the job description depicted with 1980 OCC, with 340 unique occupations reported in MIDUS1.[5] To construct polyO*NET scores tailored to individuals from MIDUS1, we calculated weighted sum of cross-walked job characteristics in MIDUS1, with the weights being the job-personality level coefficients estimated in our main analyses. The mapping of 1980 OCC to 2018 SOC can be found on the projects page (https://osf.io/tqfh5/).

2.5.5 | Exploratory analyses concerning prospective personality changes

Since our primary goal was to identify the extent to which job characteristics are linked to variance in personality development for further explanatory model development, our primary analyses used the combined sample to maximize prediction power. One important limitation to this approach is that the time ordering of the variables is ambiguous. Some participants only entered workforce at the last wave, and therefore, their personality trajectory was captured prior to employment. Thus, the results of the primary analyses cannot distinguish selection effects (i.e., personality traits shape occupational experiences) and socialization effects (i.e., occupational experiences shape personality trait).

In order to investigate the relation between job characteristics and *subsequent* personality change, we conducted exploratory analyses on a subset of participants who provided job title information and personality scores for at least two subsequent waves. This subset of the sample (extracted from Sample 1) consisted of 124 participants who reported their job titles at Wave 2, and 102 participants who reported their job titles at Wave 3. By focusing on this subset, we lose substantial statistical power, but we gain better inferential standing as the modeled personality change was entirely after starting the job. We then followed the procedures outlined in the PolyO*NET index construction section and examined the overall association between job characteristics and concurrent personality level and subsequent personality change.

3 | RESULTS

3.1 | Mean-level personality development

Table S4 displays the mean-level changes in each Big Five dimension estimated using linear growth curve models. Generally, the growth models displayed good fit (CFI >0.95), although two models in Sample 2 suggested a less than desirable fit (RMSEA >0.1). In each model, the mean slope represents the average rate of change per 2 years. We found moderate, positive growth in agreeableness in Sample 1 (M=0.63) and Sample 2 (M=0.77), conscientiousness in Sample 1 (M=0.70) and Sample 2 (M=0.66), and openness in Sample 1 (M=0.42). On the other hand, extraversion (M=−0.47 and −0.24) and neuroticism (M=−0.33 and −0.39) decreased in both samples. Importantly, both intercepts and slopes showed large variance across the Big Five, suggesting substantial individual differences in personality levels and growth that may be related to job characteristics.

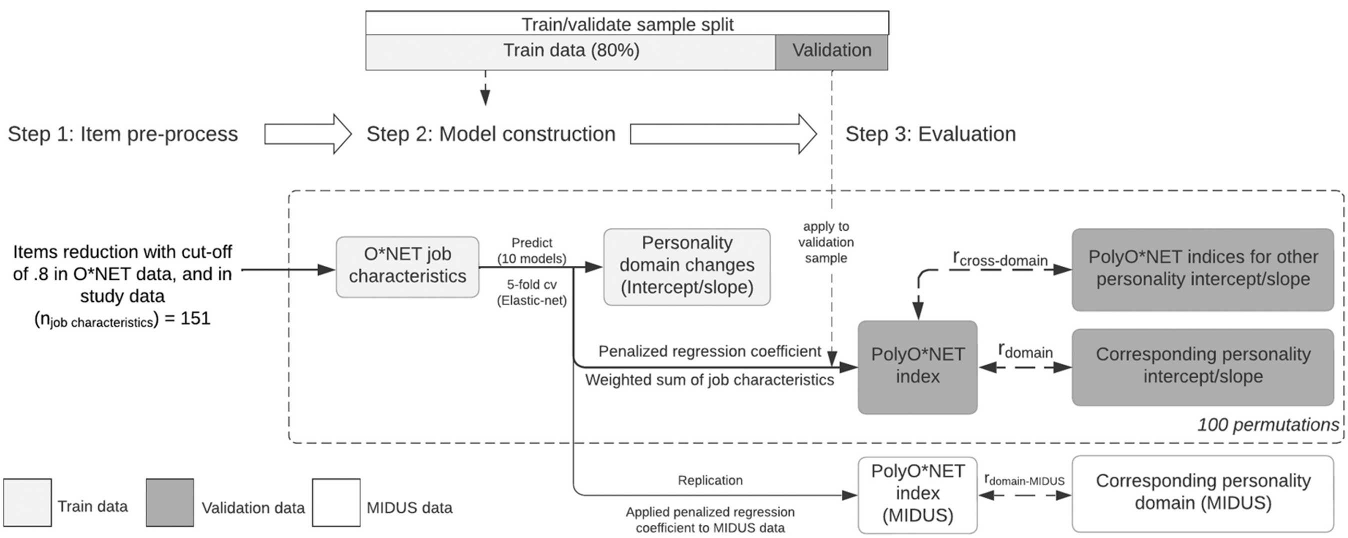

FIGURE 1 Summary schematic of the analytical approach. O*NET job characteristics were tested for association with personality intercepts and slopes using elastic net regression in the training data (80% of the sample). These associations were used to create polyO*NET indices in the validation sample (20% of the sample) or the replication sample (MIDUS) by taking a weighted sum of the job characteristics where the weights reflect the strength of association. The correlations between the polyO*NET indices and the corresponding personality intercepts and slopes were the main outcomes of interest (r_{domain}/$r_{\text{domain-MIDUS}}$). The intercorrelations between cross-domain polyO*NET indices are another outcome of interest ($r_{\text{cross-domain}}$).

3.2 | Individual job characteristics predicting personality development

To address Research Question 1, we assessed correlations of 151 job characteristics with the intercept and slope of each personality dimension (residualized for age, sex, and sample info) in the total combined sample ($N = 1054$). These results are presented in Figure 2 as a Manhattan plot. The job-personality associations varied notably across the nine job categories, with the strongest associations clustered in work context and knowledge. Individual job characteristics were generally more strongly associated with intercepts than with slopes. On average across permutations, 26.0 intercept associations and 4.8 slope associations out of the 151 possible correlates were significant at $p < 0.05$ after Meff correction for multiple testing (Derringer, 2018). The intercept of conscientiousness had the most significant associations ($Nassociations = 44$), followed by the intercept of openness (33). Among slopes, neuroticism had the most significant associations (14).

Table 1 reports the five job characteristic items most robustly associated with each personality intercept/slope across permutations from the regularized models. Characteristics from the knowledge and work-context categories accounted for 60% of the top associations. This implies that these two O*NET domains contain a variety of information relevant to personality traits. Knowledge of law was a robust predictor for the intercepts of extraversion, conscientiousness, and neuroticism, as well as the slope of neuroticism. Jobs requiring walking or running were positively associated with the intercept and slope of extraversion and negatively with the slope of conscientiousness and the intercept of neuroticism. Interestingly, work style characteristics that were developed by examining existing taxonomies of personality (e.g., Kyllonen et al., 2014) did not emerge as strong predictors of personality in theoretically expected ways. For example, jobs requiring persistence in the face of obstacles did not emerge as a top predictor for growth in conscientiousness, and jobs requiring openness to change were not robustly associated with openness. One possible explanation is that work styles were based on job incumbents' ratings, rather than expert ratings, and therefore, the ratings may reflect individual preferences to a greater extent.

3.3 | Aggregated job characteristics predicting personality development

To address Research Question 2, we examined the predictive strengths of polyO*NET indices for each Big Five trait in the held-out sample. The strongest polyO*NET-personality association was with the intercept of openness (average $r = 0.25$ across 100 permutations), followed by

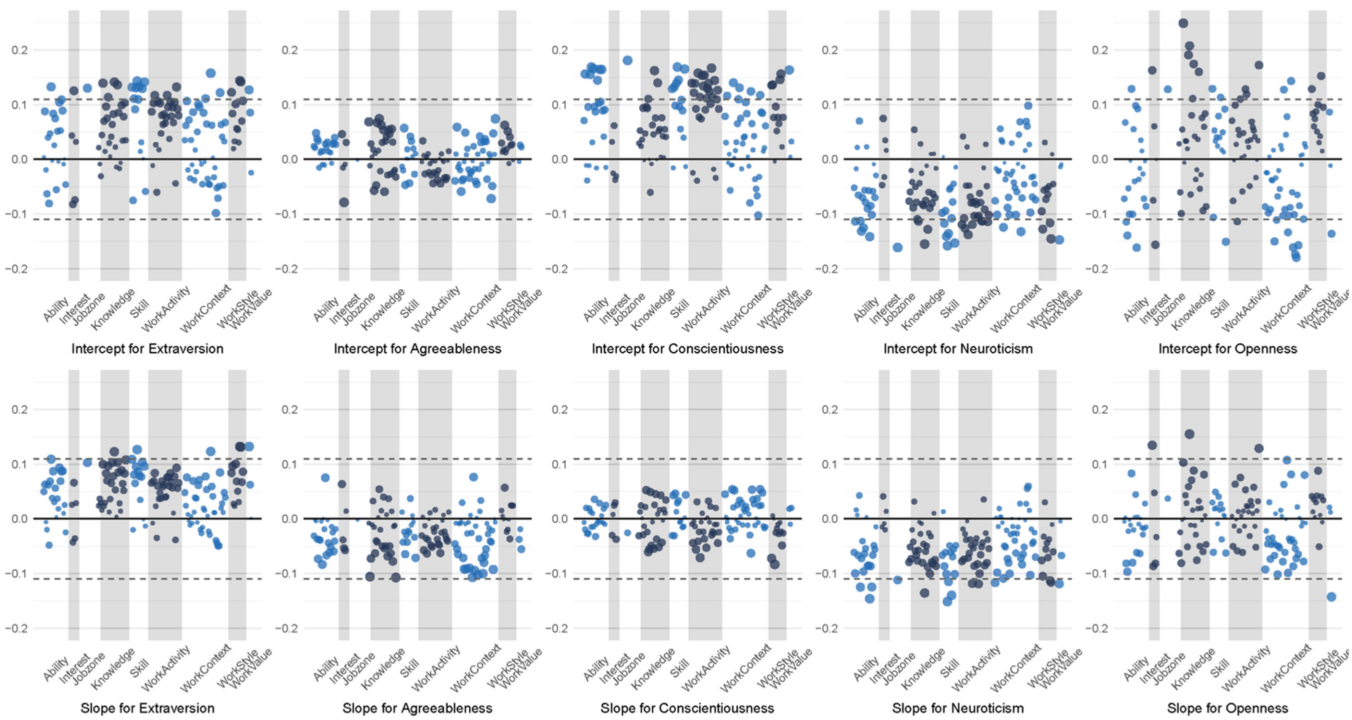

FIGURE 2 Manhattan plots for the correlation coefficients of the 151 job characteristics with personality intercepts and slopes in the combined sample. The estimates are grouped in accordance with the categories of O*NET variables. Dashed lines indicate the threshold for statistical significance after Meff correction for multiple testing (Derringer, 2018).

the intercept of conscientiousness (average $r = 0.16$) and extraversion (average $r = 0.14$). For personality changes, strongest predictions occur for openness (average $r = 0.16$), extraversion (average $r = 0.13$), and neuroticism (average $r = 0.12$). Overall, polyO*NET indices have stronger prediction for personality intercepts (overall average $r = 0.14$) than slopes (overall average $r = 0.10$). See Table 2 for more details.

3.4 | Job correlation

Next, for Research Question 3, we examined the intercorrelations among polyO*NET indices. In Table 3, the upper diagonal shows the correlations among observed personality levels and growth in the combined sample, and the lower diagonal shows the correlation among the polyO*NET indices. The polyO*NET patterns

TABLE 1 Five job characteristic items with the most robust association in regularized models for each personality trait.

	Intercept		Slope	
	Item	**Effect**	**Item**	**Effect**
E	WC: How much time in your current job do you spend walking or running?	0.16 (0.01)	KW: Knowledge of principles and methods for moving people or goods by air, rail, sea, or road	0.11 (0.02)
	KW: Knowledge of laws, government regulations, and the democratic political process	0.14 (0.01)	WS: Job requires persistence in the face of obstacles	0.13 (0.02)
	INT: Enterprising occupations frequently involve starting up and carrying out projects	0.13 (0.02)	WV: Allow employees to work on their own and make decisions	0.14 (0.01)
	WS: Job requires persistence in the face of obstacles	0.14 (0.02)	WC: How much time in your current job do you spend walking or running?	0.13 (0.01)
	WC: How important to your current job is being very exact or highly accurate?	0.12 (0.01)	KW: Knowledge of laws, government regulations, and the democratic political process	0.13 (0.01)
A	WC: How many hours do you work in a typical week on your current job?	0.08 (0.01)	KW: Knowledge of principles and methods for moving people or goods by air, rail, sea, or road	−0.11 (0.01)
	KW: Knowledge of the techniques to compose, produce, and perform art	0.08 (0.01)	AB: The ability to remember information such as words, numbers, pictures, and procedures	0.08 (0.01)
	INT: Enterprising occupations frequently involve starting up and carrying out projects	−0.08 (0.01)	WC: How often does your current job require that you be exposed to minor burns, cuts, bites, or stings?	−0.11 (0.02)
	WC: How important are interactions that require you to work with a work group or team?	−0.06 (0.01)	KW: Knowledge in the construction or repair of houses and buildings	−0.11 (0.01)
	KW: Knowledge of a foreign (non-English) language	0.07 (0.01)	WC: How often does your current job require that you be exposed to radiation?	−0.11 (0.02)
C	JZ: How much education people need to do the work, how much related experience people need to do the work, and how much on-the-job training people need to do the work	0.18 (0.01)	WS: Job requires being pleasant with others on the job and displaying a good-natured, cooperative attitude	−0.09 (0.01)
	KW: Knowledge of laws, government regulations, and the democratic political process	0.17 (0.01)	WA: Keeping up-to-date technically and applying new knowledge to your job	−0.08 (0.02)
	WA: Using control mechanisms to operate machines or processes	0.16 (0.02)	WC: How important to your current job is being very exact or highly accurate?	0.06 (0.01)
	AB: The ability to see details at close range (within a few feet of the observer)	0.14 (0.01)	KW: Knowledge of techniques and equipment for harvesting food products for consumption	0.05 (0.02)
	WS: Job requires being open to change (positive or negative) and to considerable variety in the workplace	0.14 (0.01)	WS: Job requires being open to change (positive or negative) and to considerable variety in the workplace	−0.08 (0.01)

TABLE 1 (Continued)

	Intercept		Slope	
	Item	**Effect**	**Item**	**Effect**
N	KW: Knowledge of laws, government regulations, and the democratic political process	−0.16 (0.01)	SK: Monitoring/assessing performance of yourself, other individuals, or organizations to make improvements	−0.15 (0.02)
	AB: The ability to see objects in the presence of a glare or bright lighting	−0.07 (0.01)	SK: Using scientific rules and methods to solve problems	−0.14 (0.02)
	WC: How much time in your current job do you spend walking or running?	−0.13 (0.01)	KW: Knowledge of laws, government regulations, and the democratic political process	−0.14 (0.01)
	SK: Monitoring/assessing performance of yourself, other individuals, or organizations to make improvements	−0.16 (0.01)	KW: Knowledge of principles and methods for moving people or goods by air, rail, sea, or road	−0.09 (0.01)
	SK: Managing one's own time and the time of others	−0.16 (0.01)	AB: The ability to quickly make sense of, combine, and organize information into meaningful patterns	−0.13 (0.02)
O	KW: Knowledge of the techniques to compose, produce, and perform art	0.21 (0.02)	WV: Offer supportive management that stands behind employees	−0.14 (0.02)
	KW: Knowledge of media production, communication, and dissemination techniques and methods	0.25 (0.02)	WC: How often does your current job require you to work in an open vehicle or operating equipment (like a tractor)?	−0.10 (0.02)
	WC: In your current job, how often do you wear common protective or safety equipment?	−0.17 (0.02)	KW: Knowledge of the techniques to compose, produce, and perform art	0.15 (0.01)
	WC: How often does your current job require that you be exposed to minor burns, cuts, bites, or stings?	−0.14 (0.02)	WC: How often does your current job require that you be exposed to minor burns, cuts, bites, or stings?	−0.10 (0.02)
	WV: Offer supportive management that stands behind employees	−0.14 (0.02)	WC: How often does your current job require that you be exposed to hazardous equipment?	0.11 (0.02)

Note: Effect refers to averaged correlation coefficients across 100 permutataions; The areas each item comes from is showing at the beginning of the item.
Abbreviations: A, agreeableness; AB, ability; C, conscientiousness; E, extraversion; INT, interest; JZ, job zone; KW, knowledge; N, neuroticism; O, openness; SK, skill; WA, work activity; WC, work context; WS, work style; WV, work value.

converged well with the manifest intercept and slope correlations (e.g., the association between the intercept and slope of extraversion was strong in both scenarios). However, the intercorrelations among different domains were noticeably higher when measured using polyO*NET indices than with self-report scales (average $\Delta r = 0.21$), suggesting that the job characteristics tended to capture common variance shared across personality domains. This result is consistent with job characteristics perhaps inducing correlated change in multiple personality traits.

3.5 | Replication results

To examine the robustness of our findings, we tested the generalizability of our results by replicating our findings (regarding job-personality level) using MIDUS1 sample. Consistent with our primary findings, we found modest and robust prediction of personality domains in MIDUS1 from polyO*NET indices derived from the Icelandic samples (see Table 2). Using weights estimated using combined sample, the calculated polyO*NET indices correlated most strongly with openness (0.13), followed by conscientiousness (0.10) and extraversion (0.07). The associations were slightly lower than the corresponding estimates in the Icelandic data. This could be due to several differences: the MIDUS sample was age heterogeneous across midlife (M age = 46.66 years, SD = 13.03); job characteristics may shift across chronological time, reducing the accuracy of O*NET ratings for these participants; MIDUS included jobs not found in the Icelandic samples. Yet, even with these caveats, the results indicate that some associations between work and personality are consistent across life stages, geography, and history.

TABLE 2 Predictive strength of polyO*NET scores across settings.

	E_I	E_S	A_I	A_S	C_I	C_S	N_I	N_S	O_I	O_S
RegCombined	0.14 (0.06)	0.13 (0.06)	0.01 (0.05)	0.06 (0.06)	0.16 (0.06)	−0.01 (0.06)	0.13 (0.06)	0.12 (0.06)	0.25 (0.06)	0.16 (0.07)
RegSubset	0.07 (0.10)	0.06 (0.09)	0.07 (0.09)	0.09 (0.12)	0.15 (0.11)	0.11 (0.08)	0.19 (0.09)	0.02 (0.09)	0.09 (0.10)	0.09 (0.09)
RegMIDUS	0.07	–	0.01	–	0.10	–	0.06	–	0.13	–
CorrCombined	0.16 (0.05)	0.12 (0.06)	0.02 (0.05)	0.09 (0.06)	0.19 (0.06)	−0.01 (0.06)	0.16 (0.05)	0.14 (0.07)	0.20 (0.07)	0.12 (0.07)
CorrMIDUS	0.05	–	0.02	–	0.11	–	0.06	–	0.15	–

Note: The predictive strength is the averaged Pearson correlation of the polyO*NET score in the held-out sample. The results were correlations averaged across 100 permutations (*Combined, *Subset). The standard deviation of the predictive strength is listed in the brackets. For subset analyses (*Subset), we constraint analyses on subset of participants who reported their first job titles midway, and we explored the association between polyO*NET score and subsequent personality level and change. For MIDUS replication, we used combined sample as the training sample, and we made one prediction per outcome (e.g., RegMIDUS). For the subset analyses, we com Reg*=polyO*NET scores created using elastic net regression weight; Corr*=polyO*NET scores created using bivariate correlation as weights.

Abbreviations: A, agreeableness; C, conscientiousness; E, extraversion; I, intercept; N, neuroticism; O, openness; S, Slope.

3.6 | Exploratory analyses concerning prospective personality changes

Finally, we explored the temporal association between occupational experiences and personality level and change using only personality assessments after starting the job (see Table 2 for more details). In these models, personality intercepts reflect personality levels at the wave the job was reported, and personality changes reflect development following initiating the job. Consistent with our primary findings, we found modest positive polyO*NET-personality associations with the intercept of conscientiousness (average $r=0.15$) and neuroticism (average $r=0.19$). In our subsample, change in conscientiousness showed the strongest association with polyO*NET score (average $r=0.11$). Conversely, we found only small polyO*NET-personality change associations with neuroticism (average $r=0.02$) and extraversion (average $r=0.06$). The association between polyO*NET scores and change in openness (average $r=0.09$) was smaller in terms of magnitude in this prospective analysis compared to our primary findings concerning retrospective change (cf., $r=0.16$). The association between polyO*NET scores and change in agreeableness (average $r=0.09$), on the other hand, was stronger than our primary findings (cf., $r=0.06$). Nonetheless, these results show that both selection and socialization effects stemming from occupational characteristics play a role personality development, and sampling variability could also play a role in the diverging results as well.

4 | DISCUSSION

Several studies in the past decade have connected work and personality change (e.g., Bleidorn et al., 2018; Holman & Hughes, 2021; Stahlhofen et al., 2022; Wille & De Fruyt, 2014; Woods et al., 2019; Wu, 2016). However, most previous studies have linked limited sets of work characteristics with personality traits by focusing on specific types of work characteristics in a disconnected manner. The present study addresses this research gap by examining the overall association between a holistic set of job characteristics and personality development from adolescence to early adulthood, and we further replicated our findings in a US sample focusing on midlife.

Results revealed that job titles contain information relevant for personality development. Using a combined longitudinal sample and one replication sample, we tested atheoretical associations between 151 O*NET job characteristics and personality intercepts and slopes. Individual job characteristics with the strongest personality associations clustered in work contexts and knowledge. In other

TABLE 3 Correlations among actual and expected intercept and slope scores.

	E_I	E_S	A_I	A_S	C_I	C_S	N_I	N_S	O_I	O_S
E_I	1.00	0.61	0.12	0.09	0.38	0.06	0.44	0.31	0.06	0.02
E_S	0.81	1.00	0.05	0.17	0.23	0.23	0.32	0.40	0.00	0.03
A_I	0.17	0.19	1.00	0.04	0.17	0.03	0.28	0.07	0.09	0.01
A_S	0.14	0.35	0.17	1.00	0.02	0.16	0.09	0.23	0.04	0.09
C_I	0.77	0.75	0.16	0.21	1.00	0.12	0.39	0.22	0.02	0.02
C_S	0.29	0.21	0.32	0.26	0.24	1.00	0.05	0.35	0.10	0.02
N_I	0.77	0.76	0.18	0.25	0.84	0.19	1.00	0.44	0.08	0.00
N_S	0.63	0.76	0.18	0.35	0.78	0.19	0.78	1.00	0.03	0.01
O_I	0.46	0.28	0.19	0.42	0.29	0.34	0.30	0.11	1.00	0.24
O_S	0.27	0.13	0.16	0.38	0.12	0.23	0.12	0.16	0.71	1.00

Note: Upper diagonal shows the correlation between raw intercepts (I) and slopes (S) of extraversion (E), agreeableness (A), conscientiousness (C), neuroticism (N), and openness (O) in the total combined sample, and the lower diagonal shows the average correlations among polyO*NET scores.

words, the settings in which jobs occur and the knowledge required to perform jobs tend to be most predictive of personality levels and changes over time.

Among the Big Five, the highest predictive accuracy occurred for openness in both our main and replication analyses. This finding concerning openness is comparable to previous studies using digital footprints (i.e., Facebook likes; Hall & Matz, 2020; Youyou et al., 2015). The job characteristics most associated with openness were primarily knowledge-based, so links between job characteristics and openness could emerge through preferences for cognitively demanding work. Consistent with findings from Golle et al. (2019), the current study found positive associations between job characteristics and conscientiousness, where the most robust associations were primarily ability-based. One possibility is that links between job characteristics and conscientiousness emerge through economic reinforcement toward being a reliable worker. In contrast, agreeableness was essentially unrelated to job characteristics. It is possible that idiosyncratic aspects of jobs, such as the quality of one's leader, are more highly related to levels and changes in agreeableness. Another possibility is that the current sample simply may have not included enough variability of these jobs. For example, if only jobs requiring high levels of agreeableness were included in the sample, then it would be unsurprising that we did not find associations.

Our exploratory analyses found that the highest predictive accuracy for the relationship between job characteristics and subsequent personality trajectories occurred for changes in conscientiousness. One possibility for this finding is that the demands for conscientiousness (such as being organized and systematic) are common in many job settings. To meet these demands, individuals may adjust their behavior and performance to fit the standards of their job, which could lead to short-term trait regulation and eventually long-term trait change (Wrzus & Roberts, 2017). For example, a person with low conscientiousness who is required to be organized and efficient at work may act in a more organized manner to fit better with their job. Interestingly, the association between polyO*NET scores and changes in openness was attenuated in our subset analysis, which suggests selection effects. It may be the case that pre-job openness change predicts job selection, perhaps due to changing preferences for cognitively demanding environments.

On the whole, our results provide some evidence for the predictive power of polyO*NET indices for personality. On average, associations were $r = 0.14$ with personality intercepts and $r = 0.10$ with slopes. Moreover, job characteristics important for one dimension of personality also tended to matter for other dimensions. Job demands might put pressure on multiple personality traits simultaneously, pointing to a possible avenue for correlated personality change (Allemand & Martin, 2016). Interestingly, the predictive power of the polyO*NET indices held fairly well when exported to the MIDUS sample, which comes from a different country, historical time, and period of the life span. This result implies that there are at least some links between aspects of jobs and personality that appear highly generalizable.

4.1 | The unique role of jobs for personality development research

The current analytic approach was inspired by the call for longitudinal experience-wide association studies (Bleidorn et al., 2020) and methodological innovation in behavior genetic research. The central technological advance that enabled most recent progress in behavior genetics is the ability to obtain information across the majority of the genome from one biological sample. We chose to focus on occupations as a starting point for a broad search for experiences associated with personality. People spend years preparing for their careers, and they tend to become invested in their job because it provides financial security and, hopefully, a sense of a purpose. Most importantly, matching individuals with a job to suit their skills and preferences is well-studied in the literature (e.g., Kristof-Brown et al., 2005) and holds practical value (e.g., Nye et al., 2012), yet the links between jobs and development of individual differences have been under-studied. O*NET provides a means for translating one piece of information provided by a participant into many variables, and the present work demonstrates the utility of examining and aggregating many associations to better understand adult development.

Outside of job titles, it seems unlikely that a similar technological advance is possible for most life events potentially relevant for personality development. For example, how could one gain broad sets of information about romantic relationships, life events, or stressors from a simple report? A key distinguishing feature of occupations is that they are more consistently variable than other social roles. Similar jobs tend to require similar levels of training, skills, and behaviors. For example, knowing that someone is a kindergarten teacher conveys more reliable information than knowing that they are in a romantic relationship.

Nonetheless, there are some contexts that offer opportunities to collect mass amounts of data that could be linked to personality development, such as extensive digital footprints (Youyou et al., 2015) and smartphones (Harari et al., 2016). For example, Stachl et al. used a smartphone application to collect millions of pieces of data on approximately 600 participants over 30 days. Correlations between expected personality derived from smartphone usage and self-reports of personality were about 0.40. However, Stachl et al. (2020) raised concerns about privacy due to the ability of corporations to potentially model private psychological attributes from passively (and possibly surreptitiously) collected smartphone data. Beyond this concern, generalizability may also be a problem for building cumulative knowledge using smartphones or digital footprints. For example, the fourth most important predictor of openness to ideas was the duration of a specific German newspaper application (Stachl et al., 2020). It is unlikely this variable would perform similarly in different countries. Behavior on social media may have similar limitations. Although smartphones and social media can fill time, these distractions may not have the same identity-relevance that a job holds for most people.

Given these various considerations, occupations have a unique role to play in personality development research. All researchers have access to O*NET, and the job characteristics refer to recurrent behaviors and roles that individuals enact. Thus, while other approaches are certainly valuable, we believe that occupations are uniquely poised to serve as a focal research area for cumulative personality development research.

4.2 | Strengths, limitations, and future directions

We included a combined Icelandic longitudinal sample tracking personality change across roughly a decade during the transition from adolescence to adulthood, and we also included a replication sample to add confidence in the generalizability of our findings. We used a central database, O*NET, that is available to all researchers to demonstrate a possible avenue for cumulative longitudinal experience-wide association studies of occupations (Bleidorn et al., 2020). Despite these strengths, our study has some important limitations.

O*NET ratings are not perfect indicators of people's actual job demands. The O*NET content model is based on occupations, which are broader than job titles and can vary across time periods, locations, and organizations. For example, two employees with the same occupation could experience different job demands (e.g., two therapists serving different populations). In addition, O*NET relies on expert raters and job incumbents to rate occupational characteristics. Although ratings are conducted using modern job analysis methodologies (National Research Council, 2010), it can at times be difficult to rate occupations reliably. Trained raters may differ in the extent to which they judge certain skills or abilities to be relevant to an occupation, and similarly, incumbents may perceive different work demands within the same job. Further, not all activities that occupy people's time are considered occupations, such that O*NET will not be applicable to participants outside typical paid employment.

The timing of the personality assessments and initiating the participant's job did not allow for theoretical tests of selection relative to socialization. As such, it is unclear whether the identified associations with personality slopes reflect individuals following certain personality trajectories prior to starting their jobs, whether the job socialized personality growth, or some combination of both. Our focus was on atheoretical predictive modeling. Establishing robust polyO*NET indices would allow future studies to conduct more rigorous or nuanced tests of socialization (e.g., does switching jobs lead personality changes to match the expected personality structure as implied by the polyO*NET index of the new job?).

Future work may also combine additional measures with job titles to improve predictive accuracy. For example, participants could be asked to rate how *relevant* certain job characteristics are to their work. If two participants are both managers, but one manages people in an interpersonal setting and the other in a remote, regimented manner, the types of personality-relevant experiences they encounter may be different. Additionally, factors such as investment in one's job, job satisfaction, and/or job performance may be relevant for the expectancies and values one places on work, and thus also relevant for personality development (Hudson et al., 2012; Wrzus & Roberts, 2017). Nevertheless, O*NET captures a wide variety of objective aspects of occupational characteristics that considerably expand the focus in previous studies. Both subjective rating of occupational experiences (e.g., how a person perceives the work environment), and objective prospective cues (e.g., describing situations and contexts) provide unique information to understand the dynamic nature of occupational experiences (Rauthmann et al., 2015). Specifically, examining objective job characteristics (i.e., objective aspects of the work environment, and activities) is important as these characteristics reflect everyday affordance that can be meaningful and intuitive for personality-related behaviors. Few studies examining objective job demands in comparison to subjective job demands has found that both sources of information held predictive power in work-related outcomes, such as retirement timing (Sonnega et al., 2018). Moreover, objective rating of job characteristics may provide insight into the ubiquitous institutional structure present in job markets that served as a backdrop against individual decisions (Schmitz et al., 2019). Occupational segregation based on factors such as race/ethnicity, gender, and socioeconomic status often leads to less representative groups holding jobs with fewer resources, regardless of how these demands and resources are perceived. As an example, in a study using a national representative sample, Schmitz et al. (2019) found that objective ratings of job characteristics (derived from job titles) were related to differences in individuals' sociodemographic background.

Similarly, the fit between one's personality and one's job may be important. Individuals with "fitting" personalities may have those tendencies reinforced by their job (Roberts et al., 2003). Alternatively, personality could mature more quickly when job demands are incongruent with one's personality. At least for occupational interests, individuals tend to display greater fit between their job and interests over time due to selecting new jobs, rather than jobs exerting a socialization influence on interests (Hanna et al., 2021). Each of these possibilities is worth further exploration in tandem with the vast array of job characteristics available as predictors for personality maturation.

Finally, prediction accuracy can be increased with larger sample sizes in future studies. As sample sizes increase, smaller effect sizes can be detected with greater accuracy, which will improve the performance of poly-O*NET indices (Dudbridge, 2013). Larger samples would also hopefully include coverage of a greater array of jobs, developmental periods, and historical contexts, allowing further generalizability of results.

4.3 | Conclusion

Occupations are excellent targets for cumulative longitudinal experience-wide association studies. Work is often central to one's identity, structures much of early life through education and training, and demands recurrent behaviors and roles over the course of adulthood. Jobs are well-documented, and job characteristic ratings are freely available to link with a single item of a survey. Aggregating many primary studies linking job characteristics to personality should result in stronger predictive accuracy and indices that can facilitate theoretical tests in future work.

AUTHOR CONTRIBUTIONS

Study conception and design: Anqing Zheng, Kevin A. Hoff, Alexis Hanna, D. A. Briley; Anqing Zheng, Kevin A. Hoff, Alexis Hanna cleaned the data. Anqing Zheng analyzed the data and wrote the drafts of the manuscript with the feedback from D. A. Briley. All authors contribute to revise and approve all versions of the manuscript.

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ETHICS STATEMENT

The research reported herein was approved by the University of Illinois Urbana-Champaign Ethics Committee. All data was collected in a manner consistent with ethical standards of human subjects review board. Data collection for the study was reviewed by the Icelandic Data Protection Authority in six submissions, with details provided in the supplemental materials. Data collection for the study was initially reviewed by the Icelandic Data Protection Authority on June 10, 2005 (submission number S2655: Þróun netvæddrar áhugakönnunar fyrir grunn-og framhaldsskólanema; Development of an On-Line Interest Inventory for Compulsory and Upper-Secondary Education Students). It was reviewed again on September 3, 2012; March 10, 2014; July 8, 2017; and August 3, 2018 (submission numbers S5676, S7024, S8342, S8608 with the same title: Þróun persónuleika, starfsáhuga og lífsmarkmiða meðal íslenskra ungmenna; Personality, Interest, and Life Goal Development Among Icelandic Youth).

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ENDNOTES

[1] Following the suggestion by Mõttus et al. (2020), we used the term 'predictive' to identify the relations between job characteristics and personality change that can be used to predict future phenomena, rather than implying the association necessarily identifies causal relations between our key variables.

[2] Data collection was reviewed by the Icelandic Data Protection Authority in six submissions from 2005 to 2018. Due to the continued use of these datasets and the requirement to comply with Icelandic data security regulations, these datasets are not publicly accessible at this time.

[3] The current analytical plan deviated from the original preregistration in two primary ways: first, we used regression with regularization (i.e., elastic net) rather than regularized structural equation modeling to circumvent model convergence issues and improve efficiency; secondly, in addition to using Sample 2 as training sample and Sample 1 as validation sample (as pre-registered), we also combined Sample 1 and Sample 2 and used 80% of the combined sample as our training sample and the rest as the validation sample. The first approach centers on the similarity of participants within each sample and relies on the independence of the sampling frame for the two datasets. If sample differences moderate the results, then we would expect poor portability of the poly-O*NET index from one sample to the next. The second approach ignores the distinctions between samples and uses a permutation approach (i.e., rerunning the model on many randomly selected training and testing subsets) to average over any differences. This approach assumes that the intercepts and slopes for personality reflect substantially similar constructs across samples, despite the differences in study design. Ultimately, the two approaches yielded similar results, so procedural differences did not impact results. The current paper thus focused on the averaged results of the combined sample (Approach 2), and results where we use Sample 2 as training set can be found in supplemental Table S5.

[4] We also created another iteration of polyO*NET indices in which the job characteristics are weighted by the simple bivariate correlations estimated in the training set. These two iterations yielded similar results and the current paper focused on reporting results from the elastic net regression, and results where we used bivariate correlation as weights can be found in Table 2.

[5] We did not use longitudinal design of MIDUS due to the switch of OCC system from MIDUS1 to MIDUS2, leading to unharmonized job descriptions across waves.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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